Abdihamid Yusuf MOHAMED
EFFECT OF COVID-19 ON THE PEDESTRIAN ACCIDENT SEVERITY: A CASE STUDY NEW YORK CITY
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M.Sc.THESIS

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M.Sc. THESIS

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Approval

We certify that we have read the thesis submitted by **Abdihamid Yusuf MOHAMED** titled "**EFFECT OF COVID-19 ON THE PEDESTRIAN ACCIDENT SEVERITY: A CASE STUDY NEW YORK CITY**" and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Sciences.

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Declaration

I hereby declare that all information, documents, analysis and results in this thesis have been collected and presented according to the academic rules and ethical guidelines of the institute of graduate studies, Near East University. I also declare that as required by these rules and conduct, I have fully cited and referenced information and data that are not original to this study.

Abdihamid Yusuf MOHAMED

03/07/2023

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Abstract

EFFECT OF COVID-19 ON THE PEDESTRIAN ACCIDENT SEVERITY: A CASE STUDY NEW YORK CITY. Abdihamid Yusuf MOHAMED

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This research presents the results of a study on the impact of COVID-19 lockdowns and subsequent reopenings on the number of accidents and casualties in New York City (NYC) over a 5-year period, grouped into pre-COVID-19, COVID-19, and post-COVID-19 periods. Our data was obtained from New York City accident database.

The analysis shows that in 2018, 10,811 accidents led to fatalities 21.57% and 26.65% injuries. In 2019, the accident decrease, but a rise in fatalities 23.33% even though injuries decreased to 25.45%. The year 2020 marked a significant drop in accidents to 6,540 and fatalities 18.42%, along with a sizable decrease in injuries to 16.3%. In contrast, 2021 witnessed an increase in accidents to 7,324 and fatalities 23.15%, and an increase in injuries to 18.19%. Finally, 2022 saw a further decrease in accidents, with fatalities dropping to 13.51%, and injuries decreasing to 13.39%. The study also reveals that lockdowns and reopenings have a significant impact on accidents and casualties in NYC, as shown by the continuous increase in the number of casualties and accidents during the reopening phases. The analysis of the accident indices shows that the severity of accidents that occurred between 18:00 to 6:00 is much higher than those that occurred within 12:00-17:59, despite the latter having the highest number of occurrences, also the study reveals cities which have the highest rate of accident and factors contributing the accident. Finally, the results of the study suggest that policymakers must consider the potential consequences of their decisions on public health and safety before implementing such measures.

Keywords: COVID-19; Accident severity; New York City; Lockdown;

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List of Abbreviations

WHO: World Health Organization

MVCs: Motor Vehicle Collisions

RTAs: Road Traffic Accidents

NYC: New York City

H1N1: h (aemagglutinin type) 1 and n (euraminidase type) 1

NPA: National Police Agency

PDO: property damage-only

NHTSA: National Highway Traffic Safety Administration

CRA: conventional regression analysis

RF: Random forest

LDCs: less developed countries

ANNs: Artificial neural networks

SVMs: Support vector machines (SVMs)

CHAPTER I

INTRODUCTION

1.0 Background

The COVID-19 pandemic caught the world by surprise, despite sporadic calls for pandemic preparedness (Preparedness, 2014) (Fineberg, 2014; Oxford, 2000). Unfortunately, these warnings were not compelling enough to spur world leaders into action. The last global pandemic resembling COVID-19 occurred in 1918 and was caused by the H1N1 influenza virus. Since then, six social science generations have emerged sthe following generations: the Greatest Generation (1901–1927), the Silent Generation (1928–1945), the Baby Boomers (1946–1964), Generation X (1965–1980), the Millennials or Gen Y (1981–1996), and Generation Z (1997–present). This demographic change has likely contributed to a lack of consciousness of the possibility of a global pandemic.

Lockdowns were deployed in New York City (NYC) to limit the spread of COVID-19. Such measures were unfamiliar to most people except for what they learned from literature. The effects of the lockdown on businesses and other human activities have been studied, including accidents (Bian et al., 2021) (Islam et al., 2023) (J. Li & Zhao, 2022) (Id et al., 2021) . However, there is no research on road accidents in NYC that compares conditions before, during, and after the lockdown to determine the extent of dynamic changes that occurred. Therefore, this research seeks to evaluate the effects of the COVID-19 lockdown on the severity of road accidents in NYC. The research further compares the conditions before, during, and after the COVID-19 pandemic period. A detailed investigation was also performed to identify the contributing factors, peak time, and combined effects on the severity of accidents that occurred during the periods before, during, and after the COVID-19 pandemic. The outcome of this research is expected to reveal the underlying dynamic changes that occurred as a result of the COVID-19 pandemic outbreak and provide policymakers with the required data to prepare for possible pandemic outcomes in the future.

The need for more systematic systems for accident analysis and prediction is highlighted by European road accident statistics. Road accidents are one of the major causes of death for people between the ages of 5 and 44, according to the World Health Organization. (Kapp, 2003) . According to expected trends, accidents will account for an estimated 2.4 million deaths annually by 2020, climbing to the fifth-ranking cause of death globally (WHO, 2011) .

MVCs are a different conclusion that one might anticipate being impacted by the pandemic and lockdowns for a variety of reasons. First, fewer cars on the roads are at risk of collision due to lower mobility. The lockdown and people's own worries about contracting the virus hampered people's mobility.(Goolsbee & Syverson, 2021)**,** Less traffic would give them the chance to accelerate on deserted roadways.7 8 Speeding is a significant collision risk factor that significantly increases the likelihood of serious accidents and fatalities. (Vandoros, 2020) (Inada et al., 2021). COVID-19 has increased unemployment, and there is evidence from real-world data that collisions fall off during recessions. This could be due to factors like fewer people driving to work, the cost of driving, or activities related to driving for transportation.

1.1 Problem Statement of the Study

The COVID-19 pandemic has significantly altered daily life and transportation patterns, particularly in hard-hit areas like New York City (NYC). Changes included a decrease in vehicle traffic, increased pedestrian and bicycle use, and temporary urban infrastructure modifications to accommodate social distancing. However, the impact of these changes on pedestrian safety and accident severity remains unclear. This research will study the effect of COVID-19 on the severity of pedestrian accidents in NYC, focusing on how shifts in traffic patterns and urban planning correlate with accident severity. The investigation will consider pedestrian and driver behavior, urban planning alterations, and pandemic-related regulations. The findings could inform understanding of urban mobility during a pandemic and guide future policy and planning.

1.2 Aim of the Study

The aim of a study on the effect of COVID-19 on pedestrian accident severity would be to examine how the pandemic has impacted the severity of accidents involving pedestrians.

1.2.1 Objectives of the study

The objective of this research is to establish how covid-19 affects the severity of vehicle accidents.

- To analyze accident severity before covid-19, During Covid-19 and after covid- 19.
- To calculate severity indices of pedestrian accidents at different cities in New York.
- To examine the impact of COVID-19 on the severity of pedestrian accidents, by collecting and analyzing data on accident rates and severity before, during and the post the COVID-19 epidemic
- To analyze Factors contributing to the pedestrian accident severity and the time of accident occurrence.

1.3 Research Question

1. How has the COVID-19 pandemic impacted pedestrian accident severity in New York City?
2. How was the pedestrian accident severity before COVID-19, COVID-19 and after the COVID-19 pandemic in New York City?

1.4 Significance of the Study

The importance of this study rests in its assessment of how the COVID-19 pandemic has affected the severity of pedestrian accidents in New York City. The study will offer insightful information about how the epidemic has altered the frequency and seriousness of incidents involving pedestrians. The research will help to identify the potential factors that may have contributed to changes the accident severity during the pandemic, including changes in driving behavior, changes in the types of vehicles on the road, changes in infrastructure, and changes in weather patterns.

Furthermore, this study will provide essential information regarding the factors that affect the severity of accidents in New York City. This information can then be used to guide the formulation of safety measures and policies aimed at reducing both the frequency and severity of accidents throughout the city.

1.5 Scope of the Study

This study aims to ascertain the impact of the COVID-19 epidemic on the frequency of pedestrian accidents in New York. The analysis of accident severity before, during, and after the COVID-19 pandemic will be the main emphasis of the research, which will also look at accident incidence, severity, and type. In order to understand the variation in accident severity across the city, the study will also compute severity indices of pedestrian accident at various cities in New York City. By gathering and analyzing data on accident rates and severity before, during, and after the pandemic, this study will look at how COVID-19 affected the severity of automobile accidents. During the COVID-19 pandemic, changes in driving habits, the kinds of vehicles on the road, infrastructure changes, weather patterns, and the effects of public health initiatives are other potential contributing factors that the research will also identify. The scope of the investigation will be restricted to the vicinity of New York City and the pandemic's time period.

1.6 Limitation of the Study

The study on the effect of COVID-19 on pedestrian accident severity in New York City may be limited by several factors, including the data availability, data accuracy, temporality, sample size, external factors, causality and data analysis. The availability of data on pedestrian accidents in New York City may be limited, which can affect the scope and completeness of the study. Additionally, the accuracy of the data may be a concern and may affect the validity of the findings. The study will also be limited by its temporal scope, only being able to analyze data from specific time periods during the pandemic, before and after, which may not capture the full extent of the impact. As a small number of participants may not be representative of the population and may not be generalizable to other regions or historical periods, it could simply be a limitation. External factors such as changes in weather patterns, road conditions, or infrastructure may also affect accident severity. The study will also be limited by the ability to establish causality between the impact of COVID-19 and the accident severity, as it will be based on observational data. The methods used for data analysis may also affect the interpretation of the result.

CHAPTER II

Literature Review

2.0 Introduction

This chapter provides some background information on the literature that is currently available regarding the impact of COVID-19 on the seriousness of pedestrian accidents. The first section focuses on Overview of COVID-19 Pandemic. The second deals with Overview of accident studies of COVID-19 pandemic, the third explain accident severity, and the fourth explain factors influencing accident severity. The fifth section focuses on factors influencing accident severity, while the sixth models used in the analysis of accident severity, finally, the seventh section deals analysis of COVID-19 lockdown in New York.

2.1 Overview of COVID-19 Pandemic

In December 2019, a pneumococcal outbreak was discovered in Wuhan, China. Since then, it has been discovered to be a brand-new, contagious coronavirus, or COVID-19 (Shi et al., 2020) The World Health Organization (WHO) proclaimed COVID-19 a pandemic on March 11, 2020, following its alarming rate of global spread. (Aslani, 2020) (WHO, 2020Governments are making unprecedented efforts to slow the virus's spread in the hopes of finally bringing the pandemic under control.

The COVID-19 pandemic caught the world by surprise, despite sporadic calls for pandemic preparedness (Preparedness, 2014) (Fineberg, 2014; Oxford, 2000). Unfortunately, these warnings were not compelling enough to spur world leaders into action. The last global pandemic resembling COVID-19 occurred in 1918 and was caused by the H1N1 influenza virus. Since then, six social science generations have emerged. One of the early American epicenters of the COVID-19 pandemic was New York City. On March 2, 2020, the city's first case was determined.

2.2 Overview of accident studies of COVID-19 pandemic

This section examines current research on how the COVID-19 pandemic affects accident severity. (Vandoros, 2021) analyzed the effects of the pandemic on motor vehicle accidents (MVAs) and related outcomes in Greece using data from 2015 to 2020. The first lockdown period in March and April 2020 saw a decline in crashes, fatalities, and minor and serious injuries, which trended following the lockdown albeit to a lesser amount. According to the findings, there was a significant drop in all four outcomes (collisions, fatalities, serious, and minor injuries) during the lockdown period when compared to prior years, with a 49.49% drop in MVAs, a 53.13% drop in fatalities, a 53.20% drop in minor injuries, and a 38.96% drop in serious injuries. A difference-in-differences econometric analysis and an interrupted time-series analysis supported these findings and showed that the decline in MVAs lasted after the lockout. (Vandoros, 2022)

The effect of lockdown on traffic collisions, injuries, and fatalities in Bangladesh from January 2016 to March 2020 was examined in a linked study. 20,527 injuries, 23,111 fatalities, and 12,471 traffic crashes were all reported throughout the monitoring period. Basic time series plots showed that accidents, injuries, and fatalities dropped off during lockdown. Overall, the study discovered that throughout the lockdown, different regions of the nation had various patterns of road traffic collisions. (Islam et al., 2023). The patterns of MVAs, fatalities, and injuries during the COVID-19lockdown in Maharashtra, India, as compared to the times of regular traffic conditions, were analyzed in a different study conducted there. According to the data, there were 88.6% fewer MVAs on average per day during the lockdown than there were in 2018.

The third phase had the largest average daily number of MVAs, but this increase was seen during all of the lockdown phases.

In less developed nations (LDCs), pedestrians in particular are seen as the most vulnerable road users. According to the World Bank, around 70% of all traffic-related fatalities worldwide occur in LDCs, and 65% of those deaths involve pedestrians. (Montgomery & Roberts, 2008) A recent research of the severity of traffic injuries in

Dhaka, Bangladesh, also discovered that the likelihood that a collision involving pedestrians will result in a fatality is 3.7 times higher. (Sharmin, 2018)

On another hand, (Barnes et al., 2022), An academic study examines how the COVID-19 lockout affected car accidents in Louisiana, USA. The authors present graphical evidence of the lockdown's impact on various collision types and calculate the drop in accidents using a regression discontinuity design. They discover that almost all crash types—with the exception of those involving pedestrians and fatalities—saw a considerable decline. The findings point to an increase in accident severity. Furthermore, the authors calculate that the lockout saved Louisiana $289.6 million and almost $21 billion nationally (USA) in costs related to fewer traffic accidents. The frequency of accidents involving alcohol and driver attention reduced after the lockout, while those involving drug use did not. The authors conclude by looking at how the lockdown differed depending on the driver characteristics and contributory factors. (Barnes et al., 2022).

In their review, (Shaik & Ahmed, 2022), studied how COVID-19 affected travel patterns and road traffic safety. The COVID-19 social shutdown restrictions are credited with reducing driving accidents, particularly those with minimal or minor injuries, according to the study. However, the rate of serious and fatal fatalities increased, much as the reviews mentioned above. Because safety awareness, mobility, and mobility patterns were related, the study found that COVID-19 had an indirect effect on the number of accidents. The results also demonstrated a reduction in accident fatalities and injuries due to rigorous shutdown limitations and high levels of residential movement. The article comes to the conclusion that COVID-19 has significantly harmed road traffic safety. Approach behavior had a substantial impact on the consistency of mobility throughout the COVID-19 outbreak, and attitudes about the disease had a direct bearing on changes in activity-travel behavior. (Shaik & Ahmed, 2022).

2.3 Accident Severity

The impact of an accident and its repercussions are greatly influenced by the accident severity. The World Health Organisation (WHO) estimates that road traffic accidents cause up to 50 million injuries and 1.35 million fatalities annually, making them the largest cause of death and injury globally. According to the rules, a traffic accident is defined as an unforeseen, unplanned event that involves a moving vehicle, with or without the involvement of other road users, and that causes fatalities as well as property damage.

According to the reported severity of the injuries involved, the National Police Agency (NPA) of Japan generally classifies traffic accidents into three severity levels: minor, severe, and deadly. Therefore, these same three accident severity levels are used as dependent variables in the current study (Hyodo & Hasegawa, 2021)

The degree of accidental loss can be used to gauge it. Four levels of severity classification are used.

- Minor injuries: These are injuries that typically occur in less severe crush accidents and they may not require hospitalization and can often be treated with first aid measures, such as ice packs and pain relievers.
- Moderate injuries: These are injuries that typically occur in more severe crush accidents and may include fractures, dislocations, and internal injuries. They require medical attention and may involve hospitalization for treatment and observation. Moderate injuries may also require surgery to repair broken bones or damaged tissues.
- Severe injuries: These are injuries that typically occur in the most severe crush accidents and can be life-threatening. They may include head trauma or spinal cord injuries.
- Material losses, which inevitably result in accidents that also result in material losses.

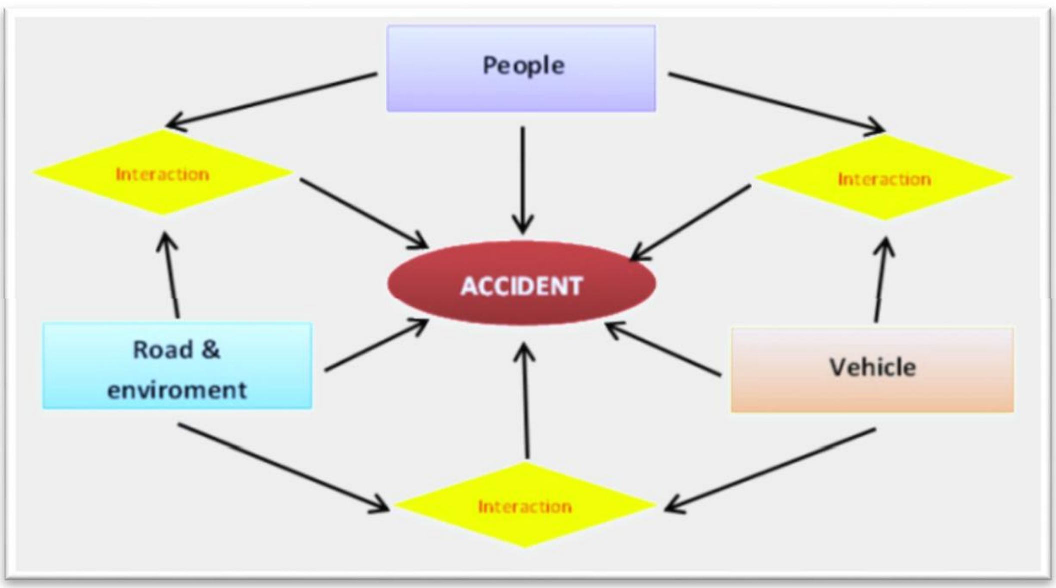
2.4 Factors affecting traffic accident

A number of factors, both internal and external to the vehicle, might cause a traffic accident. The human factor—the individuals who utilize the transportation infrastructure and who direct how a vehicle and its driver move—is one of the internal components. Internal elements include those related to the vehicle, the road, and the surroundings. The main causes of accidents are these three elements (Halim et al., 2017).

Other causes of traffic accidents include the interaction of multiple elements, in addition to the three primary causes. Two or more of these components may be combined to create the interaction. It is evident from the image below (Vandoros & Papailias, 2021)

Figure 1

The Cause of the Accident and their Interactions



2.4.1 Alcohol

The model recognized alcohol as one of the elements influencing crash severity. From 2000 to 2004, about 5% of all accidents involved alcohol. By crash severity, however, the percentage of alcohol-related crashes varies greatly. The percentage of alcohol use increases as the severity level rises. In PDO collisions, the percentage of alcohol use is around 5%, but it rises to nearly 40% in fatal crashes.(Zhang, 2010)

Further research was done to better understand the relationship and the factors influencing it because crashes involving alcohol are strongly associated to crash severity.

2.4.2 Over speeding

One of the main contributing factors to crash severity was also found to be speed. The speed increases as the severity level does. The average travel speed in fatal crashes was 53 mph, which was 23 mph faster than the PDO crashes and 10 mph faster than severe injury crashes. It shows that speed has a significant impact on crash severity, with high speed conditions having more severe consequences than low speed conditions (Zhang, 2010).

Significant traffic infractions, such as speeding (most frequently), driving against the light, and failing to stop at intersections where halting is required, account for the majority (60%) of Swedish driving licence revocations. The number of people in Sweden who had their driving privileges revoked in 2020 was at an all-time high; as a result, total speed has increased (Kong et al., 2020)

2.4.3 Distracted driving

It has become well recognised that distracted driving endangers traffic safety. It negatively affects driving ability, lengthens reaction times, and impairs control of the vehicle; as a result, it accounts for 25% of serious motor vehicle accidents and causes high morbidity and fatality rates. When driving while inattentive or concentrating on something else while doing so, such as talking, smoking, texting, applying makeup, reading, eating, or using a mobile phone, is referred to as distracted driving (Halim et al., 2017).

Both distracted driving and driver inattention have existed since the development of automobiles. (Regan et al., 2011) Due to the widespread use of numerous in-vehicle electronic devices, such as cellphones, navigation support systems, easily accessible internet devices, and onboard entertainment systems in addition to the traditional sources of distracted driving (such as eating, drinking, and/or applying makeup), distracted driving has gotten worse in recent years along with technological advancements. (Voinea et al., 2023) Subsequently, distracted driving and drivers' inattention have become major contributing factors in vehicle crashes (Alosco et al., 2012) and they have a higher likelihood of producing disastrous crash consequences (Lym & Chen, 2020).

2.4.4 Red light jumping

Red light jumping, also known as running a red light, refers to the act of a driver crossing an intersection while the traffic signal is red. The motorist and other drivers on the road are both at risk of serious harm or death as a result of this risky and illegal behavior.

The National Highway Traffic Safety Administration (NHTSA) reports that one of the main factors contributing to intersection-related accidents in the US is running red lights. In fact, the NHTSA estimates that red-light running results in around 700 deaths and 137,000 injuries every year.

There are several reasons why drivers might run red lights. One of the most common reasons is impatience. Drivers who are in hurry or running late may try to save time by running red lights instead of waiting for the signal to change. Other drivers may be distracted or unaware of the traffic signal because they are using their cell phone, adjusting the radio, or engaging in other distracting behaviors.(Jh, 2006)

Regardless of the reason, running red lights is illegal and dangerous. In addition to putting themselves and other road users at risk, drivers who are caught running red lights can face serious consequences. These consequences may include fines, points on their driving record, and even license suspension or revocation.(Jh, 2006)

To solve the issue of running red lights, many cities have implemented red light cameras at intersections. These cameras automatically photograph drivers who run red lights, and the images can be used to issue tickets and fines. Some studies have shown that the presence of red light cameras can reduce red light running and intersection-related accidents.(Franklin, 2020) red light jumping is a dangerous and illegal behavior that puts both drivers and other road users at risk.

2.4.5 Weather conditions

Weather conditions can play a significant role in causing accidents on roads, particularly in areas with harsh or unpredictable weather patterns. In this literature review will briefly discuss the research that has been conducted on the relationship between weather conditions and road accidents, including the causes and consequences.

Several weather conditions can lead to accidents on the road, including heavy rain, snow, ice, fog, and wind. These conditions can make it difficult for drivers to see the road or other vehicles, reduce the traction of the tires, and make it more challenging to control the vehicle. In addition, extreme weather conditions can increase the likelihood of other hazards, such as fallen trees or debris on the road, which can further contribute to accidents.(Malin et al., 2019)

The consequences of accidents caused by weather conditions can be severe. A National Highway Traffic Safety Administration (NHTSA) research found that weather-related factors account for around 22% of all traffic accidents in the country, causing an average of 5,000 fatalities and 418,000 injuries annually (NHTSA, 2019). Accidents brought on by meteorological conditions can result in major economic expenditures, including property damage, medical expenses, and missed productivity, in addition to causing physical harm (Useche et al., 2018).

2.4.6 Road condition factors

Several road condition factors can contribute to accident severity, including road surface conditions, road geometry, signage, and lighting. Poor road surface conditions, such as potholes, cracks, or uneven surfaces, can reduce the traction of the tires, leading to loss of control and accidents. Similar to how poor signs and illumination make it harder for drivers to see the road or other cars, it can also impair visibility, raising the risk of accidents (By, 2021).

The consequences of accident severity due to road conditions can be severe Approximately 27% of all traffic fatalities in the US are attributed to poor road maintenance and design, finds a research by the National Highway Traffic Safety Administration (NHTSA) (NHTSA, 2018). Accidents brought on by poor road conditions can affect people physically, but they can also have a huge financial impact, including missed wages, property damage, and medical expenditures.

2.5 Models used in the analysis of Accident Severity

The examination of accident severity employs a variety of models, some of which include:

1. Logistic regression: An analysis of the relationship between a dependent variable and one or more independent variables is done statistically using logistic regression. The accident severity is the dependent variable in a study of accident severity, while the independent variables can include things like weather, road conditions, vehicle type, and driver behavior (Al-ghamdi, 2002)

The following two are the most significant:

a) A continuous response variable is required for CRA, and
b) In CRA, the response variables may have nonnegative values.

(Jovanis & Chang, n.d.) In their investigation, which used Poisson regression as a method of accident prediction, they discovered a number of issues with the use of linear regression. For instance, they found that the variance of accident frequency grows as vehicle-kilometers travelled. As a result, this analysis breaks the linear regression's homoscedasticity assumption.

In a concise survey of the models used to estimate the frequency of accidents, (V. Shankar et al., 1997) cite: "The use of linear regression models is inappropriate for making probabilistic statements about the occurrences of vehicle accidents on the road."

They demonstrated that the negative binomial regression is a potent predictor and one that ought to be used more frequently in next studies on accident frequency.

(Al-ghamdi, 2002) created a logistic model to predict the probability that drivers are to blame in crashes involving cyclists. Age of the driver, rider age (squared), cyclist alcohol usage, cyclists making turning motions, and rural areas are covariates that raise the likelihood that the driver is at fault.

2. Decision trees: A common machine learning method for categorizing data into different groups is decision trees. Decision trees can be used to pinpoint the elements most likely to increase the severity of an accident in the context of accident severity analysis (W. Shankar & Mannering, 1995) used a tiered logic formulation to determine the likelihood of an accident occurring and the likelihood of its severity. According to the study, if at least one driver was not using a restraint system at the time of the accident, there is a higher likelihood of evident injury or fatality relative to no visible harm.

3. Random forests: A technique for ensemble learning called "random forests" entails building numerous decision trees and aggregating their forecasts. Random forests can be used to pinpoint the most significant causes of accident severity in the context of accident severity analysis.

A data mining technology called random forest (RF) is used to address issues with classification and regression. Classification accuracy has increased dramatically as a result of voting to choose the class type and ensemble tree growth. These ensembles are grown by creating random vectors. Every tree is created using a random vector. Classification and regression trees make up RF. Analyzing tree output allows for the solution of classification issues. The RF forecast is determined by the majority of class votes. Since over-fitting does not occur in big datasets, the generalization error merges to a limiting value when additional trees are added to the RF (Dogru, n.d.)

4. Artificial Neural Networks: Machine learning algorithms called neural networks are modelled after the structure and operation of the human brain. Neural networks can be used in accident severity analysis to find patterns in the data that are not immediately obvious.

A natural neural network is made up of many interconnected neurons, and artificial neural networks (ANNs) attempt to mimic this behavior. An ANN is a group of nodes that converts the weighted sum of input values into an output value of "0" or "1". The weighted total is typically converted to the output of each node using a sigmoidal transfer function. Input nodes in neural networks are equal to the number of inputs, while output nodes are equal to the number of classes divided by the number of outputs (Dogru, n.d.) If there are two classes, just one output node is required. Multi-layer perceptrons are ANNs that have numerous layers. Input nodes and hidden layer nodes are completely interlinked, while output nodes and hidden layer nodes are connected to one another. In addition to these links, one of the input nodes has a direct connection to the output node. In ANN, each connection between nodes carries a weight (Ghomi & Hussein, 2022).

5. Support vector machines: Data is categorized into two or more categories using a form of machine learning algorithm called support vector machines. The factors that are most likely to increase an accident's severity can be found using support vector machines in the context of accident severity analysis.

Due to their remarkable accuracy and capacity for handling massive, high-dimensional data sets, support vector machines (SVMs), which were just recently invented, are garnering interest from researchers.(Omar, 2020) The SVM method has been used in a variety of applications, including event detection, trip time prediction, traffic speed and flow prediction, and eye movement detection (Ma et al., 2009).

The linear separation of complex data sets is not feasible. Data that cannot be separated in a linear fashion can be mapped onto a new dimension and then separated in a linear fashion. By creating linear borders on mapped samples, kernel functions are utilized to locate the boundary's optimal placement. In the original sample space, a complex curve is required to distinguish between two classes, but after projecting the original sample values onto a better feature space, a linear decision boundary can be used to distinguish between the two classes. As a result, the classification problem becomes the challenge of identifying an appropriate transformation (Ayton et al., 2019).

6. Bayesian Networks: These models can be used to determine the causal links between an accident's severity and its many contributing variables. Bayesian Networks can assist model and predict accident severity more precisely by taking into account uncertainty and relationships between variables.

Bayesian networks have gained popularity during the past ten years as a representation for expert systems to use when encoding uncertain expert information. Numerous fields have used it, including medicine, document categorization, information retrieval, image processing, data fusion, and decision support systems (Editor-in-chief et al., 2004)

Some researchers used a Bayesian network to analyse traffic accidents. (Mujalli & On, 2011) employed a Bayesian network to determine the variables influencing injury severity, which was divided into killed/severely injured and mildly injured categories. The accident type, driver age, lighting, and number of injuries were found to be the factors related with a killed/severely injured accident based on the Bayesian network. The findings suggest that a Bayesian network may graphically describe complicated systems with interconnected components and make predictions without the use of assumptions. (Editor-in-chief et al., 2004) built a Bayesian network to analyse the severity of the injury. The findings demonstrated that modelling of traffic accidents may be done using a Bayesian network.

(Ozbay & Noyan, 2006)'s A Bayesian network was built and then used to anticipate incident duration and comprehend the elements influencing incident clearance time. The findings suggested that a Bayesian network can capture the incident's random nature. (Gregoriades & Mouskos, 2020) The importance of employing a Bayesian network to model traffic accidents was emphasized, as was the need to model the effects of the potential contributing elements rather than view traffic accidents as a deterministic assessment problem.

2.6 Analysis of COVID-19 lockdown in New York

One of the early American epicentres of the COVID-19 pandemic was New York City. The city enacted rigorous lockdown procedures to stop the virus's spread, which included the closure of non-essential businesses, schools, and public gatherings. The lockdown measures began in mid-March 2020 and continued for several months, with some restrictions slowly easing up over time.

The virus's ability to spread in New York City was effectively stopped by the lockdown procedures. Early in April 2020 saw a high in the number of daily new cases, which then gradually decreased over the ensuing months. The number of daily new cases had decreased to a few hundred by the end of June 2020 from a peak of over 10,000 in early April.

However, the lockdown measures had a significant economic impact on the city. Many businesses were forced to close, and many New Yorkers lost their jobs. The unemployment rate in New York City soared to over 20% in April 2020, up from around 4% in February 2020.

Table 1.

NYC COVID-19 pandemic lockdown and reopening timeline key events

11 January 2020	First COVID-19 death reported in China
21 January 2020	The first case of COVID-19 reported in the United States.
29 February 2020	The first COVID-19 death reported in the United States.
1 March 2020	The first COVID-19 case in the state of New York
March 12, 2020	Events with more than 500 people must be canceled or postponed
March 12, 2020	Broadway shuts down
March 14, 2020	First two COVID-19 deaths in NYS

March 16, 2020	NYC public schools are closed down
March 17, 2020	Bars and restaurants in NYC closed, except delivery
March 22, 2020	All non-essential employees must remain at home as the NYS on Pause Program begins.
March 28, 2020	Governor Cuomo stops all unnecessary construction projects in New York State
March 31, 2020	NYC exceeds 1,000 COVID-19 deaths
April 15, 2020	Gov. Cuomo mandates the use of face masks or covers in public Areas
April 30, 2020	Governor Cuomo announces midnight to five in the morning Subway closures in New York City.
May 23, 2020	Governor Cuomo approves social gatherings of no more than 10 People.
May 27, 2020	U.S. COVID-19 deaths pass 100,000
June 8, 2020	NYC's Phase 1 reopening has begun.
June 22, 2020	NYC's phase 2 reopening has started.
July 6, 2020	U.S. COVID-19 deaths surpass 130,000
July 6, 2020	Phase 3 of NYC's reopening begins without indoor dining
July 19, 2020	Phase 4 of NYC's reopening begins, excluding malls, museums,and indoor restaurants and bars.
July 24, 2020	NYC reports 227,517 COVID-19 cases and 22,934 deaths to date
September 2, 2020	NYC gyms reopen, while indoor group exercise and swimming

	pools remain closed.
September 9, 2020	NYC malls reopen with 50% of their original patronage and noindoor eating. With 25% of their original patronage, casinos reopen all around New York State.
September 29, 2020	Elementary students at NYC's public schools return to classes.
September 30, 2020	NYC's indoor dining is back, with a 25% availability restriction.
October 5, 2020	In NYC, there have been 252,000 COVID-19 incidences and 23,861 deaths.
November 19, 2020	NYC schools switch to all-remote

CHAPTER III

METHODOLOGY

3.0 Overview

In order to conduct this research, data was extracted from the NYC Motor Vehicle Collisions – accident database, which is based on police-reported motor vehicle collisions in NYC (NYPD, 2023). The dataset contains 1.9 million rows of data, and data from January 1, 2018 to December 31, 2022 was used for this study. Three periods were classified: pre-COVID-19 (2018-2019), COVID-19 lockdown (2020-2021), and post-COVID-19 (2022).

3.1 Overview of the Case Study Area in (NYC)

New York City (NYC) is the largest city in the United States (US), the combination of its population; economic significance, cultural influence, and infrastructure contribute Boasting a population of more than 8 million, New York metropolis is regarded as the biggest metropolis in the United States and one of the most populated cities in the world. On the American east coast, it is situated in the state of New York. Lankevich, G. (2023, May 26). New York City. Encyclopedia Britannica. https://www.britannica.com/place/New-York-City

Five boroughs make up New York City: Staten Island, Brooklyn, Queens, and Manhattan. Each borough has an own personality and attractions. Manhattan is known for its skyscrapers, Broadway theaters, and high-end shopping, while Brooklyn is known for its vibrant arts and music scene. Queens is home to several museums and cultural institutions, and the Bronx is known for its parks and the famous Bronx Zoo.

Transportation in NYC is primarily by subway and bus, although taxis and rideshare services are also popular. The city is a significant international gateway thanks to its many large airports, including John F. Kennedy International Airport and LaGuardia Airport.

Figure 2

New York City Map from Google

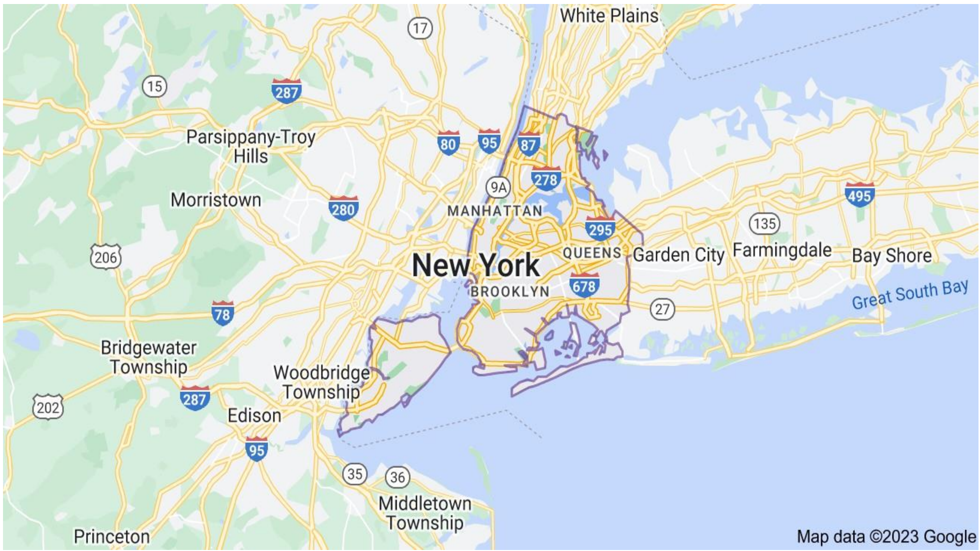


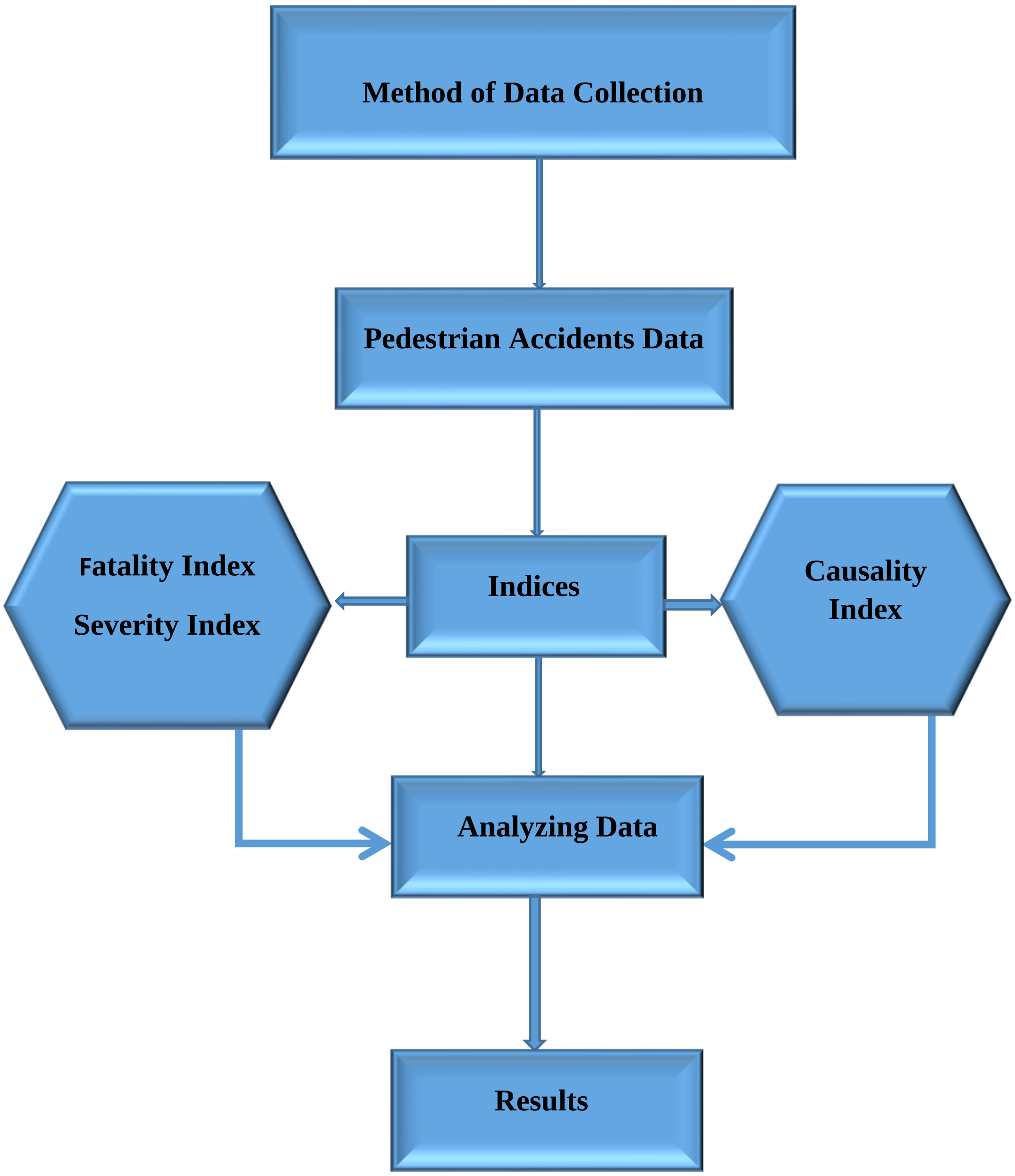
Figure 3

New York City Road Map from Google

3.2 Data Collection

Figure 4

Follow chart of methodology



3.3. Data preparation process

Data collection procedures will involve collecting and organizing relevant data sources, as well as analyzing the data with severity indices formulas to identify trends and patterns in accident severity. This includes analyzing the severity of accidents that occurred before, during, and after the COVID-19 pandemic, as well as investigating the potential relationships between accident severity and various COVID-19-related factors. The appropriate open-source database for NewYork State provided the data.

https://data.cityofnewyork.us/Public-Safety/Motor-Vehicle-Collisions-Crashes/h9ginx95 and organized in excel by using severity indices formula to analyze pedestrian accident data that occurred in New York City in the last five years. Excel will be used for creating visual representations of data, such as charts and graphs, making it a useful tool for data visualization. Also accident time will be classified as having occurred in the daytime (6:00 a.m.–6:00 p.m.) at night (6:00p.m.–6:00 a.m.) (Pathak & Chandrasekaran, 2023).

3.4 Analysis of accident magnitude

Severity indices will be used to measure the severity of pedestrian accidents and the resulting injuries or fatality. Three indices will be used to assess the effects of the COVID-19 pandemic lockdown on accident severity in NYC: accident causality, fatality, and severity indices. These indices are defined below.

Accident causality index is a measure that reflects the severity of road accidents by considering the number of fatalities and injuries in relation to the total number of accidents that occurred. It is calculated by dividing the total number of fatalities and injuries resulting from a road accident by the total number of accidents that occurred. The CI can be calculated for a specific period of time, such as a day or a year. The CI takes into account both fatalities and injuries, and is often used as an indicator of the overall safety of a particular area or activity.

The accident causality index is an important tool for evaluating the safety of road transport systems and identifying areas for improvement.

Casualty index $= \frac{C}{A}$ Equation (1)

Where C = sum of fatality and injury, and A = total accident

Accident fatality index is a measure that reflects the severity of road accidents by considering the number of fatalities in relation to the total number of accidents that occurred. It is calculated by dividing the total number of fatalities resulting from a road accident by the total number of accidents that occurred. The accident fatality index is an important tool for evaluating the safety of road transport systems and identifying areas for improvement. A higher accident fatality index indicates that a greater proportion of accidents resulted in fatalities.

Fatality index $= \frac{F}{A}$ Equation (2)

Where F= number of fatalities

Accident severity index is a measure that assesses the severity of road accidents by taking into account the number and severity of injuries and fatalities that occurred in each accident. This index provides a more detailed picture of the consequences of accidents than the simple count of accidents or fatalities. Accident severity index is an important tool for identifying areas with a high incidence of severe accidents and developing targeted interventions to improve road safety.

Severity index $= \frac{F}{A}$ Equation (3)

3.5 Factors Influencing Accident Severity

Factors influencing accident severity can be driver-related factors, vehicle-related factors, environmental factors, and other external elements can all be generically categorized (Eboli et al., 2020)

The dataset contains several factors that contribute to accidents. These factors will be grouped into ten categories; each of them will be named with an F-prefix, with no particular naming convention following. The results will be analyzed with respect to the time block and year. A radar plot will be used to visualize the leading factors and the proportion of accidents that result in injury or fatality for the three periods under review.

CHAPTER IV

RESULTS AND FINDINGS

4.0. Introduction

This chapter presents the results of accidents that occurred over a 5-year period in the study area. The years have been grouped into pre-COVID-19, COVID-19, and post-COVID-19 periods to analyze the trends. The pre-COVID-19 period spans from 2018 to 2019, the COVID-19 period with lockdown is characterized by 2020 to 2021, and the post-COVID-19 period is represented by the year 2022.

4.1 Severity Analysis of pedestrian Accident

The study is utilizing three different mathematical formulas to calculate the accident severity; they are three different equations that are suitable for calculating the accident severity according to (Emenalo et al., 1977) used these equations in Analysis of road traffic accidents.

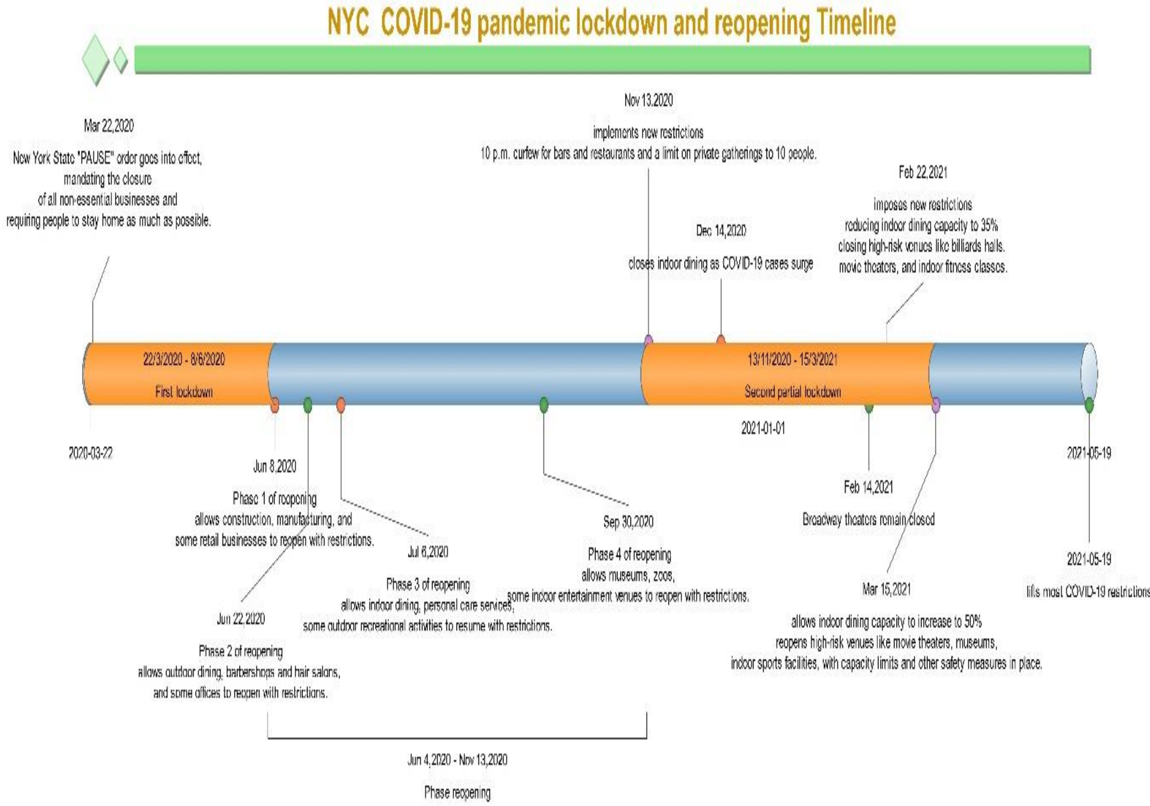
The pedestrian accident severity in the study is analyzed using the following parameters which also include the three severity indices define in the previous chapter

- Number of Injury: This refers to the number of injuries resulting from an accident.
- Number of Fatality: This refers to the number of fatalities resulting from an accident.
- Casualty Index: is a measure that reflects the severity of road accidents by considering the number of fatalities and injuries in relation to the total number of accidents that occurred.
- Severity Index: is a measure that assesses the severity of road accidents by taking into account the number and severity of injuries and fatalities that occurred in each accident.

4.2. Time series of key events during the COVID-19 pandemic in NYC

Figure 5

NYC COVID-19 pandemic timeline



The first verified COVID-19 case is reported on March 2, 2020, in New York City. The initial shutdown took place from March 22, 2020, through June 8, 2020. Due to the COVID-19 pandemic, a "pause" order was put into effect in New York City on March 22, 2020. This directive commanded non-essential enterprises to close and urged citizens to remain at home. The goal was to stop the virus's spread and keep the healthcare system from being overburdened. The closure of businesses had a significant economic impact, causing job losses and revenue decline. New Yorkers were advised to only leave home for essential activities, and gatherings were discouraged. Enforcement involved fines and increased police presence. While controversial, the order led to a decline in COVID-19 cases and hospitalizations**.**

Phase one reopening: on June 8, 2020 phase one reopening started, including building, manufacturing, fishing, forestry, agriculture, and some types of retail that allow curbside pickup.

Phase two reopening: June 22, 2020 businesses, including restaurants with outdoor seating, barbershops, offices, real estate agencies, in-store retail, car dealerships, retail rentals, repair shops, and management organizations for commercial buildings, have reopened.

Phase three reopening: July 6, 2020 permits 50% indoor seating at pubs and restaurants, as well as personal care services.

Phase four reopening: September 30, 2020 allows museum, zoos and some indoor entertainment venues to reopen with restrictions. (Wang & Noland, 2021)

On November 13, 2020, new restrictions were implemented, including a 10:00 p.m. curfew for bars and restaurants, as well as a limitation on private gatherings to 10 people.

Again between November 13, 2020-March, 15, 2021 second partial lockdown started. On February 14,2021theaters remain closed. On February 22, 2021, new restrictions were imposed, which included reducing indoor dining capacity to 35% and closing high-risk venues such as billiards halls, movie theaters, and indoor fitness classes.

On March 15, 2021, indoor dining capacity was allowed to increase to 50%, and high-risk venues such as movie theaters, museums, and indoor sports facilities were reopened with capacity limits and other safety measures in place (Huang & Li, 2022)

On May 19, 2021, most COVID-19 restrictions were lifted.

4.3 Number of causality and causality index

4.3.1 pre-COVID-19, during COVID-19 and post COVID-19

Table 2.

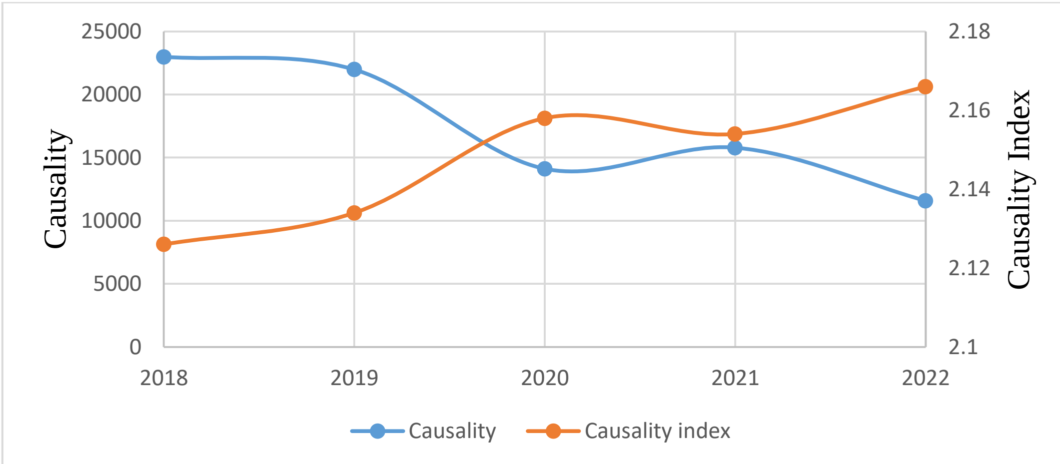
Number of causality and causality index between 2018 and 2019

Years	Causality	Causality Index
Pre-COVID-19		
2018	22986	2.126
2019	21980	2..134
Sub-total	**44966**	**4.26**
COVID-19		
2020	14118	2.158
2021	15782	2.154
Sub-total	**29900**	**4.31**
Post-COVID-19		
2022	11579	2.166

This table above shows the 'Causality' and 'Causality Index' across five years (2018 to 2022): 'Causality' appears to be decreasing overall from 2018 to 2022, with a small increase in 2021 compared to 2020. The decline from 2018 to 2020 was significant (approximately 39%), after which there was a 12% increase in 2021, and then another decline by 27% in 2022. The 'Causality Index' shows a gradual increase from 2018 to 2022. The rise is consistent but modest, with a percentage increase of around 1.9% from 2018 to 2022. In general, the trends suggest that as 'Causality' decreased, the 'Causality Index' increased.

Figure 6

Number of causality and causality index between 2018 and 2022



4.4. Number of Fatality and Fatality Index

4.4.1 Pre COVID-19, COVID-19 and post-COVID-19

Table 3. *Fatality and fatality index in 2018-2022*

YEARS	FATALITY	FATALITY INDEX
	Pre-COVID-19	
2018	246	0.022
2019	266	0.026
Sub-Total	**512**	**0.049**
	COVID-19	
2020	210	0.032
2021	264	0.036
Sub-Total	**474**	**0.068**
	Post COVID-19	
2022	**154**	**0.03**

This table provides outlines of Fatality and Fatality Index from 2018 to 2022.

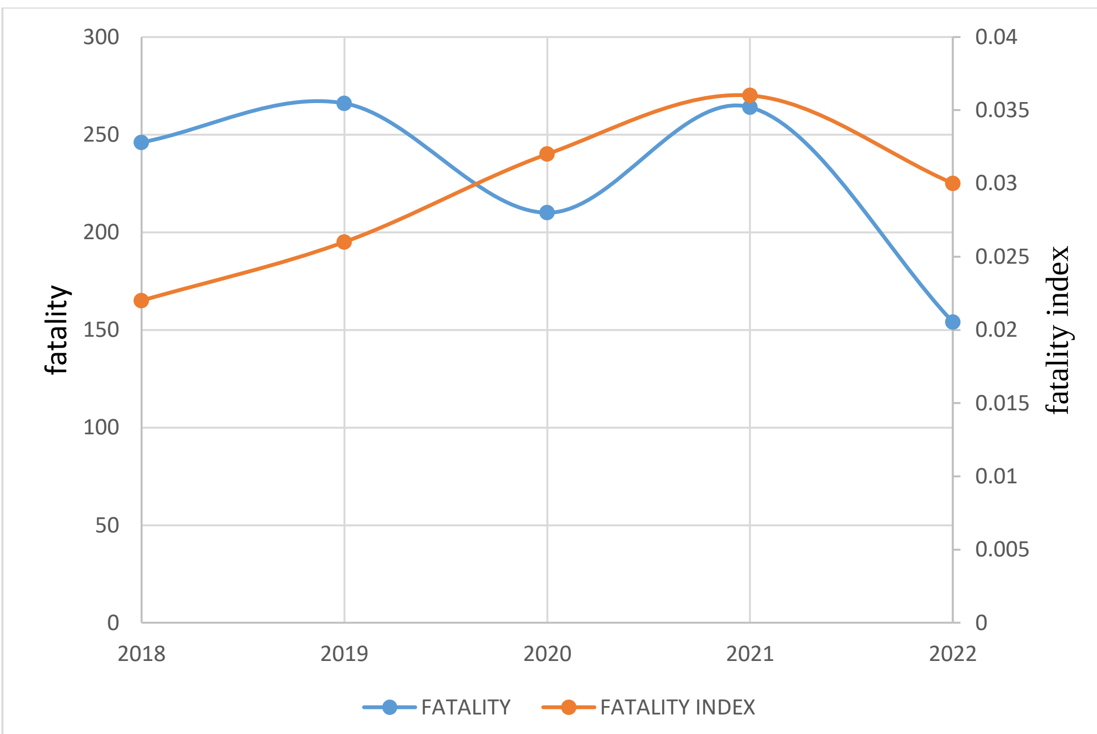
The data tells that fatality increased from 2018 to 2019, then decreased in 2020, rose again in 2021, and then saw a significant decrease in 2022.

In the years 2018 to 2021, we see that the Fatality Index generally increases, even though the raw number of fatalities decreased from 2019 to 2020, the Fatality Index increased, indicating a more substantial decrease. The trend continued into 2021, where both the Fatality Index and the number of fatalities increased.

In 2022, however, we see both the number of fatalities and the Fatality Index decrease. This suggests that in 2022, the rate of decrease in the denominator (whatever it may be) was similar to or less than the rate of decrease in fatalities.

Figure 7

Number of fatality and fatality index between 2018 and 2022



4.5. Number of Accident and Severity Index

4.5.1. Pre-COVID-19, during COVID-19 and post-Covid-19

Table 4.

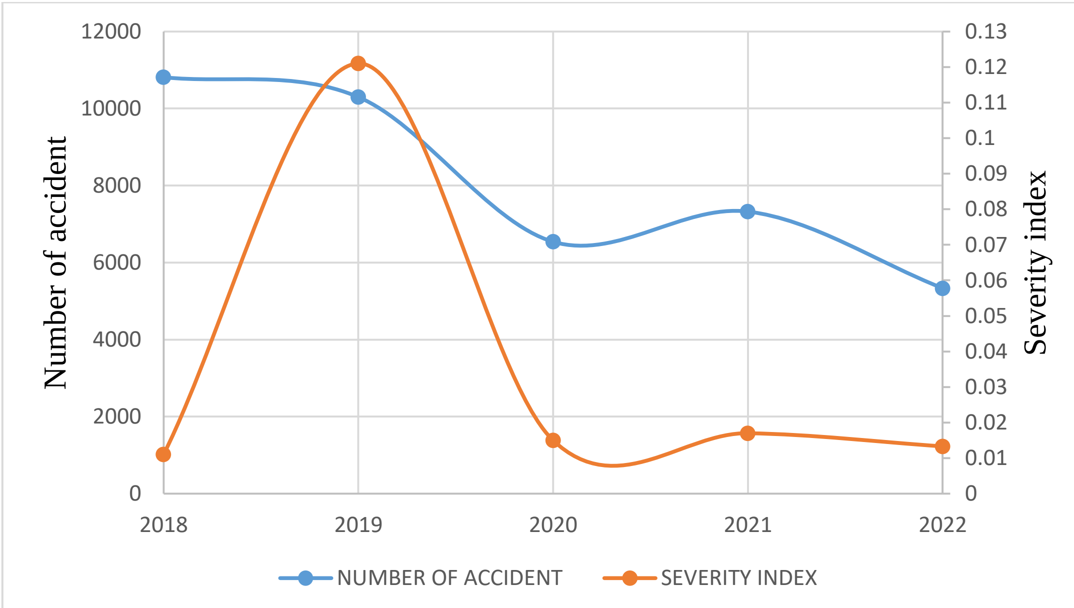
Number of accident and severity index between 2018 and 2022

Years	Number of Accident	Severity Index
	Pre-COVID-19	
2018	10811	0.011
2019	10297	0.121
Sub-total	**21108**	**0.132**
	COVID-19	
2020	6540	0.015
2021	7324	0.017
Sub-total	**13864**	**0.032**
	Post-COVID-19	
2022	5334	0.0133

The above table presents a record of accident occurrences and corresponding severity indices from 2018 to 2022. In 2018, there were 10,811 accidents with a low severity index of 0.011. In 2019, the accidents dropped to 10,297, but the severity index shot up to 0.121, indicating more severe accidents despite fewer occurrences. 2020 saw a drastic reduction in accidents to 6,540, with a 36% decrease from the previous year, and a lower severity index of 0.015, potentially due to COVID-19 travel restrictions. 2021 had a slight increase in accidents to 7,324 and a minor rise in the severity index to 0.017 as restrictions eased. The year 2022 experienced the lowest accident frequency of 5,334, with a slight decrease in severity index to 0.0133. Despite fewer accidents, the severity remains a concern.

Figure 8

Number of accident and severity index between 2018 and 2022



4.6. Number of injuries between 2018 and 2022

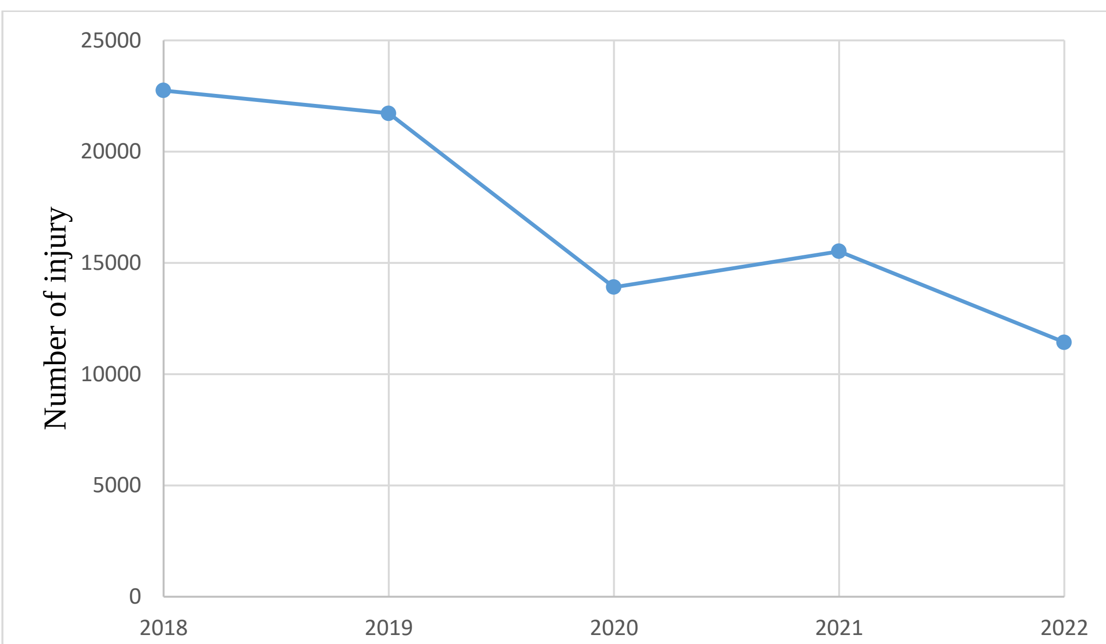
Table 5. *Number of accidents, fatality and injury over the 5years*

Years	Number of injury
Pre COVID-19	
2018	22740
2019	21714
Sub-total	**44454**
Covid-19	
2020	13908
2021	15518
Sub-total	**29426**
Post-COVID-19	
2022	11425

Between the years 2018 and 2022, there was a notable decrease in the number of injuries reported each year. The year 2018 recorded the highest number of injuries with a total of 22,740. However, in 2019, this figure dropped slightly to 21,714, showing a reduction of approximately 4.5%. The most significant reduction was experienced in 2020, with 13,908 injuries reported, which marks a decrease of nearly 36% from the previous year, possibly a result of the worldwide COVID-19 pandemic and the subsequent restrictions. In 2021, the number of injuries slightly rose again to 15,518, an increase of around 11.6% from 2020, suggesting a gradual return to pre-pandemic activity levels. However, the trend of reducing injuries resumed in 2022 with only 11,425 reported injuries, approximately a 26.3% decrease from the preceding year, pointing to an overall improvement in safety measures, changes in behavior, or variations in data collection and reporting methods.

Figure 9

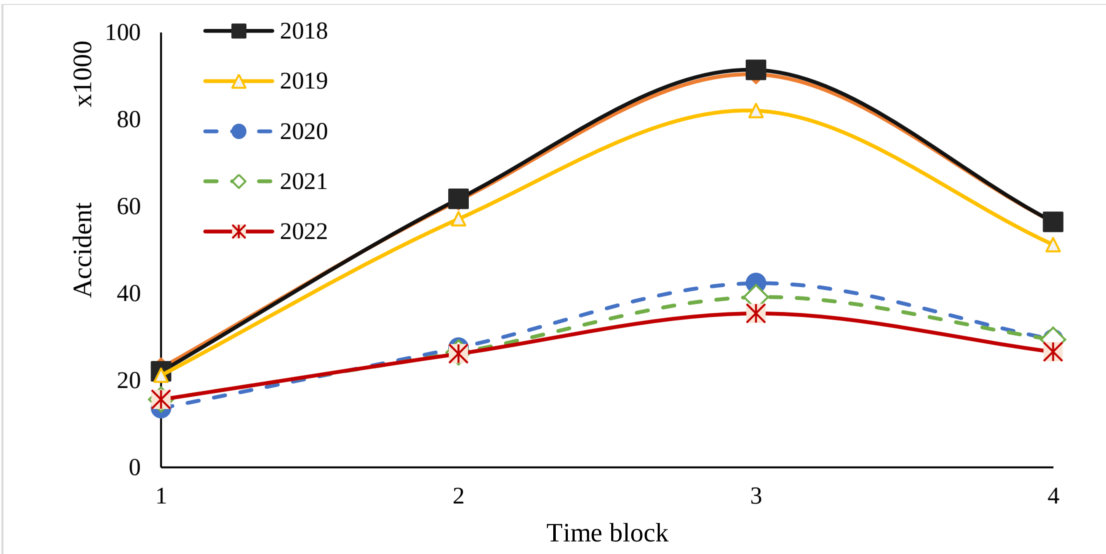
Number of injuries over the 5years



4.8 Time of accident occurrence

Figure 10

Variation of number of accidents with time between 2018 and 2022



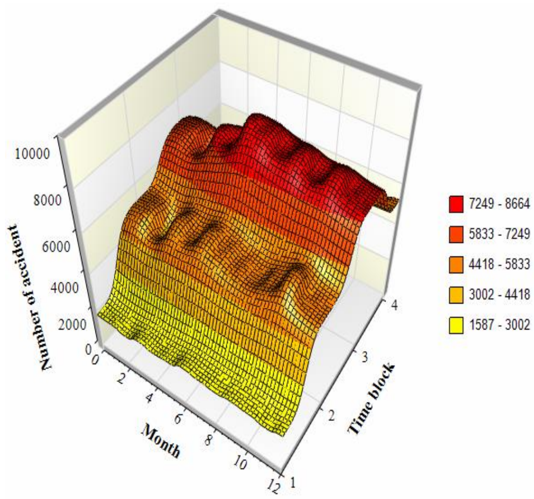
Furthermore, Figure 11 below shows a 3-D plot of the number of accidents versus the month and time block, which indicates that the pattern of accident occurrence in NYC with respect to the period and time of occurrence did not significantly change. While one could argue that the 3-D plot for the year 2020 is different, it is noteworthy to point out that the impact of COVID-19 (including public perception) in the study area became more of a reality after March 1, 2020, when the first confirmed case was reported by the New York Time (Goldstein & McKinley, 2020)

Additionally, fears of an index case in New York were evident as early as February 1, 2020, following the first reported COVID-19 death on January 11, 2020, and the confirmation of the United States' first index case on January 21, 2020 (Goldstein, 2020; Taylor, 2020). All of these factors may have contributed to the slight drop in the number of accidents in January 2020 compared to those of the pre-COVID-19 period.

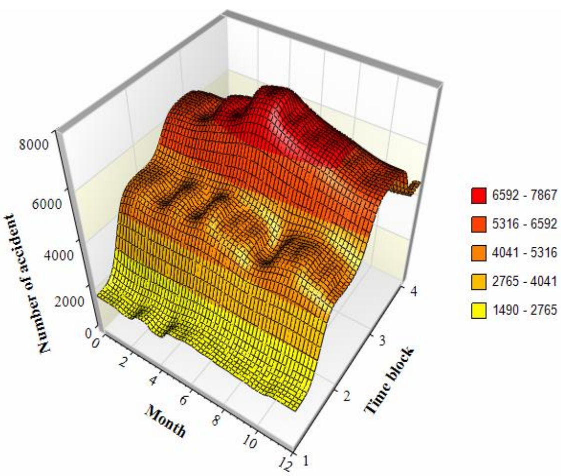
Figure 11 a, b, c, d and e

3D plot of the number of accidents versus the month and time block

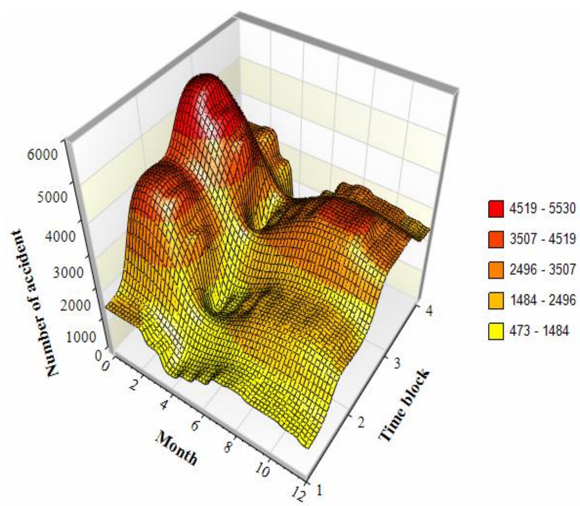
2018 (a)



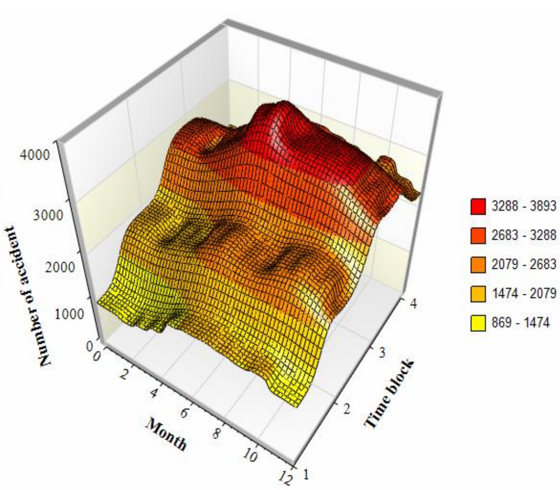
2019 (b)



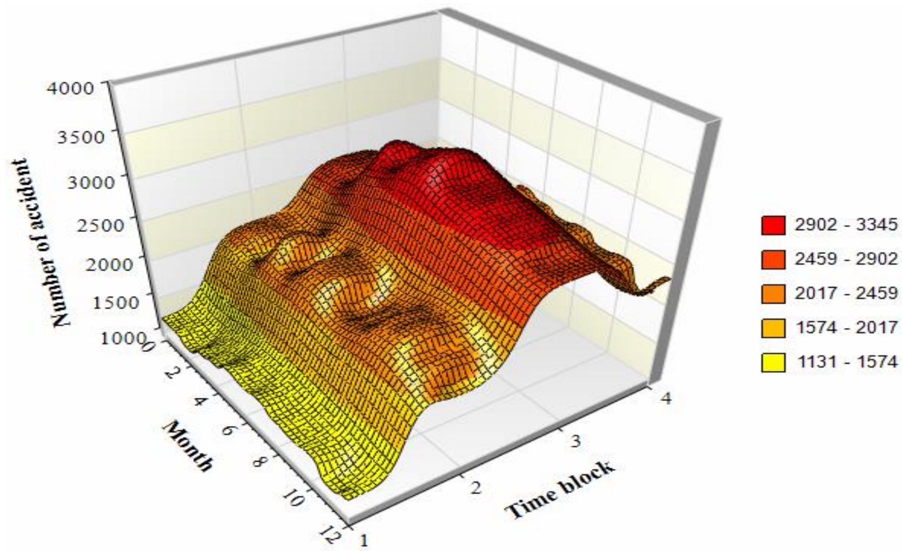
2020 (c)



2021 (d)



2022 (e)



Clearly, the number of accidents during the evening rush hour in NYC reaches its peak with in the third time block (12:00 to 17:59). It is also noteworthy to point out that the annual accident peak in NYC takes place during the Spring Festival, which includes the Tribeca Film Festival, the New York International Auto Show, and the Cherry Blossom Festival at the Brooklyn Botanic Garden, the Five Boro Bike Tour, the Governors Ball Music Festival, and other events. Some of these festivals, such as the Five Boro Bike Tour, can draw up to 30,000 participants and span across all five boroughs of New York City.

The first lockdown in the State of New York was implemented on March 22, 2020 at 8 PM through Executive Order 202.8, which modified Executive Order 202.6 and placed restrictions on all businesses and not-for-profit entities (L. Li et al., 2021). (New York, 2020) This resulted in the trough observed in Figure 4.8.1 above in 2020, which occurred between late March and May. By April 2020, the number of casualties in NYC had reached its lowest point across all time blocks.

The analyzed data demonstrates that lockdowns and reopenings have a significant impact on accidents and casualties in NYC. For instance, in September 2020, further reopening measures were implemented, including the reopening of gyms, malls at 50% capacity, casinos, public elementary schools returning to class, and indoor dining at up to 25% capacity, which resulted in another increase in casualties. This reopening allowed more people on the road, hence the increase.

4.9 Factors contrinuting to accident

The dataset contained several factors that contributed to the accidents. These factors were grouped into ten categories, listed in Table 1, each named with an F-prefix, with no particular naming convention followed. The comprehensive results of the influence of these factors on the injuries and fatalities of pedestrians . The results were analyzed with respect to the time block and year. A radar plot was used to visualize the leading factors and the proportion of accidents that resulted in injury and fatality for the three periods under review.

Table 6.

Accident contributing factors

Code	**Description**	**Data Identified Factors**
F1	Driver condition	Fatigued/Drowsy Fell Asleep Illness Lost Consciousness Physical Disability Prescription Medication
F2	Driver behavior	Aggressive Driving/Road Rage Alcohol Involvement Backing Unsafely Cell Phone (hand-Held) Cell Phone (hands-free) Driver Inattention/Distraction Driver Inexperience Drugs (illegal) Eating or Drinking Failure to Keep Right Failure to Yield Right-of-Way

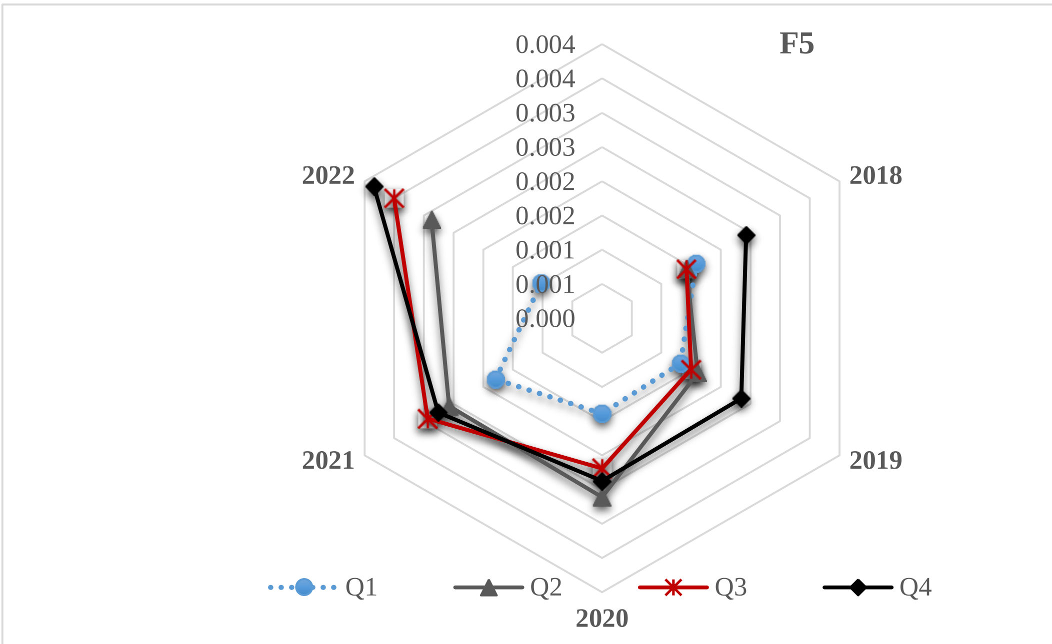
		Following Too Closely Listening/Using Headphones Outside Car Distraction Passing or Lane Usage Improper Passing Too Closely Reaction to Other Uninvolved Vehicle Reaction to Uninvolved Vehicle Texting Turning Improperly Unsafe Lane Changing Unsafe Speed Using On Board Navigation Device
F3	Driverless/Runaway Vehicle	Driverless/Runaway Vehicle
F4	Weather/Environmental factors	Animals Action, Glare
F5	Obstructions/ Road design and infrastructure	Lane Marking Improper/Inadequate Obstruction/Debris Pavement Defective Pavement Slippery Shoulders Defective/Improper Traffic Control Device Improper/Non-Working Traffic Control Disregarded View Obstructed/Limited
F6	Vehicle properties	Accelerator Defective Headlights Defective Other Electronic Device Other Lighting Defects

		Oversized Vehicle Steering Failure Tinted Windows Tire Failure/Inadequate Tow Hitch Defective Vehicle Vandalism Windshield Inadequate Brakes Defective
F7	Unspecified	Unspecified
F8	Other Vehicular	Other Vehicular
F9	Passenger Distraction	Passenger Distraction
F10	Pedestrian and bicycle behavior	Pedestrian and bicycle behavior

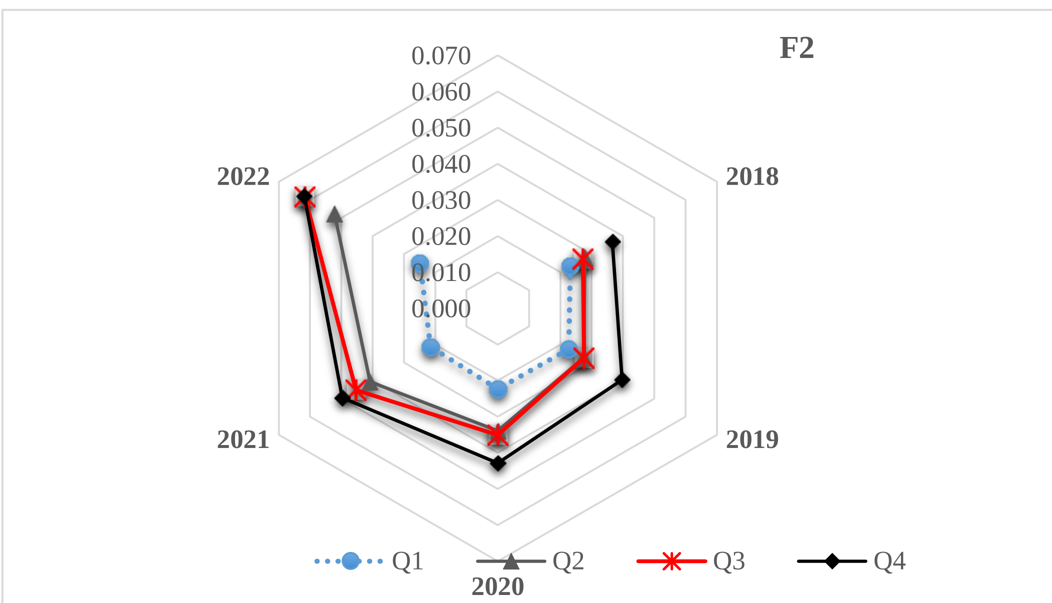
The effects on pedestrian injury and fatality: The results presented in Figure 11 below show that F2 (driver behaviour) and F7 (unspecified factors) were the leading causes contributing to accidents resulting in pedestrian injury, followed by factors related to obstruction and road infrastructure. Moreover, these accidents tended to occur mostly between 12:00 and 23:59, which was also observed for other factors. Specifically, the critical time period for high pedestrian injury was identified as 18:00 to 23:59. The proportion of accidents resulting in pedestrian injury was similar in the pre-COVID-19 and lockdown years. Furthermore, from Figure 11a, the ratio of the number of injuries to accidents did not exceed 4% for the pre-COVID-19 and lockdown year. However, a change in dynamics was observed from 2021, and in 2022, the number of injuries to accidents rose beyond 6% for F2 as a contributing factor. Similarly, the changes observed with F5 and F7, from pre-COVID-19 and lockdown years to 2022, were from 0.2% to 0.4% and from 2% to 2.5%, respectively.

Figure 12 F5 (a), F2 (b), F10 (c) and F7 (d)

Radar plot of the ratio number pedestrain injury to accident.

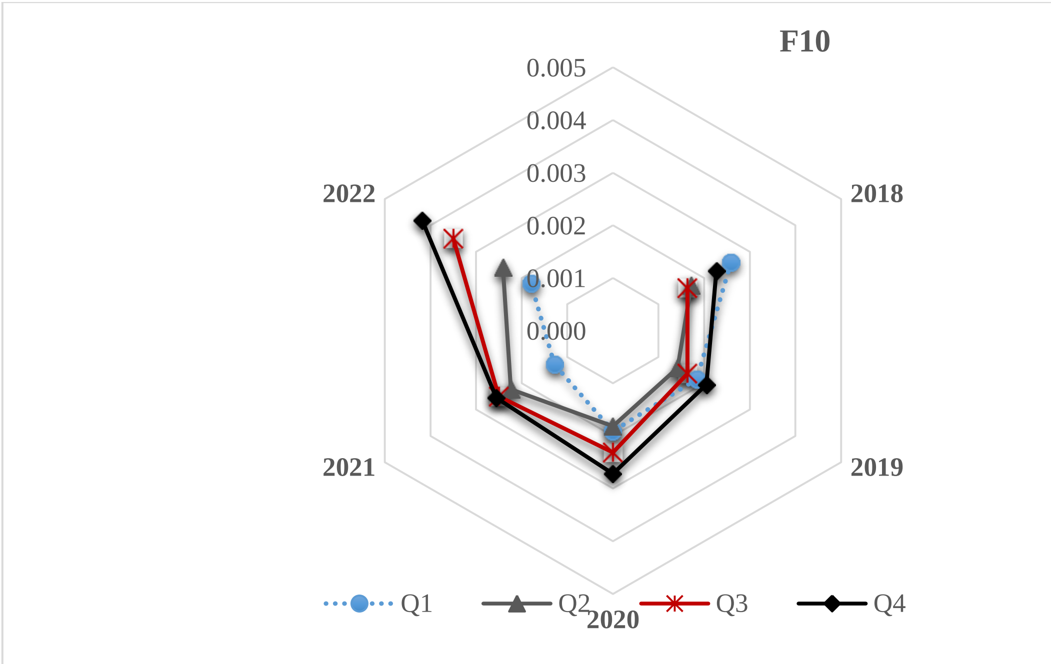


F5 (a)

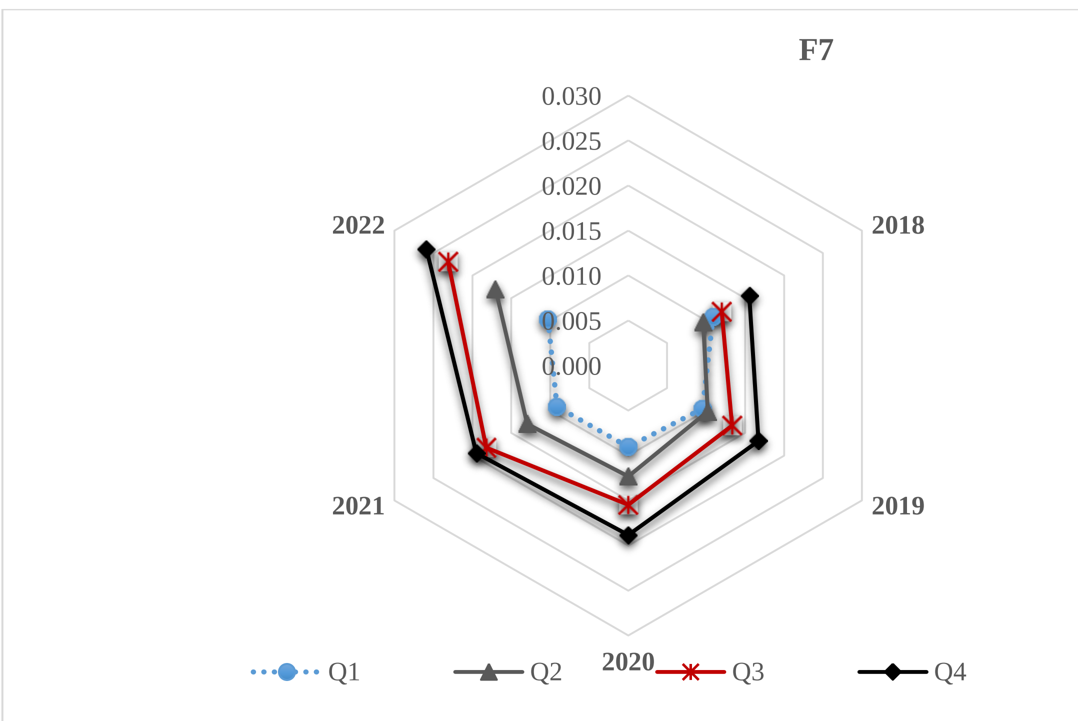


F2 (b)

F10 (c)


F10
0.005
0.004
0.003
0.002
0.001
0.000
2018
2019
2020
2021
2022
Q1
Q2
Q3
Q4

F7 (a)

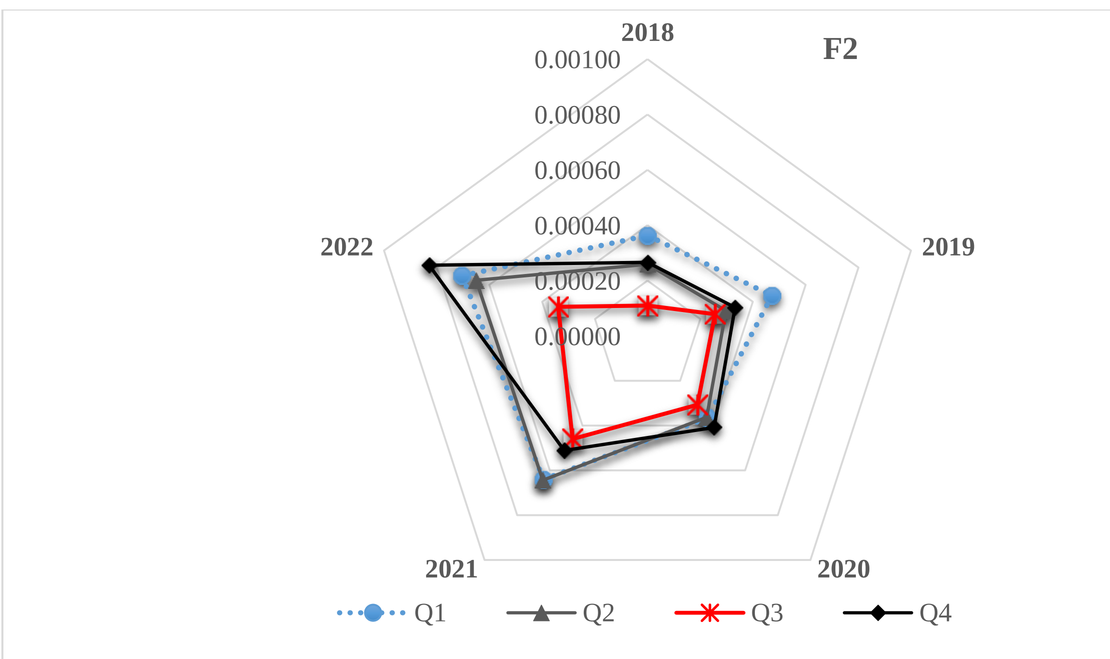

F7
0.030
0.025
0.020
0.015
0.010
0.005
0.000
2018
2019
2020
2021
2022
Q1
Q2
Q3
Q4

The results presented in Figure 13 below indicate that the time block between 00:00-05:59 had the highest rate of the number of fatalities to the number of accidents for accidents resulting in pedestrian fatalities, with F2, F5, F7 and F10 being the leading contributing factors. In 2020, during the peak of the COVID-19 pandemic and lockdowns, driver behavior contributed to a lower number of accidents resulting in pedestrian fatalities. However, in 2022, the highest number of pedestrian fatalities was recorded, with driver behavior as a contributing factor. The other factors show a different pattern; the pandemic and lockdown year (2020) recorded a higher number of pedestrian fatalities with respect to the number of accidents.

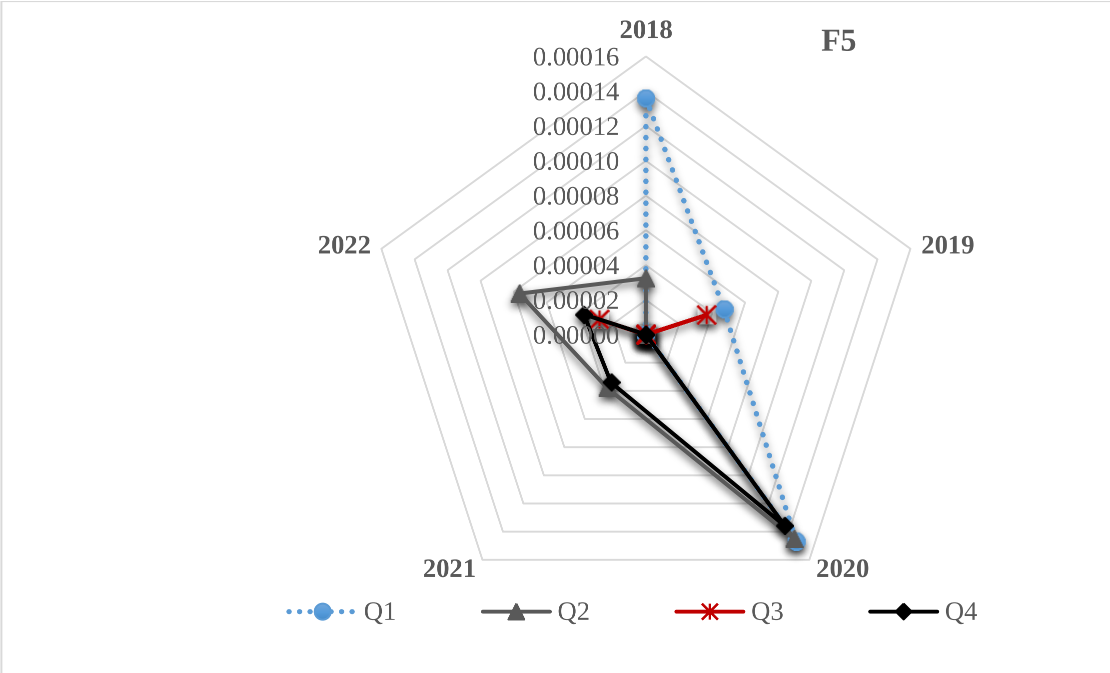
Figure 13 F2 (a), F5 (b), F7 (c) and F10 (d)

Radar plot of the ratio number pedestrain fatality to accident.

F2 (a)

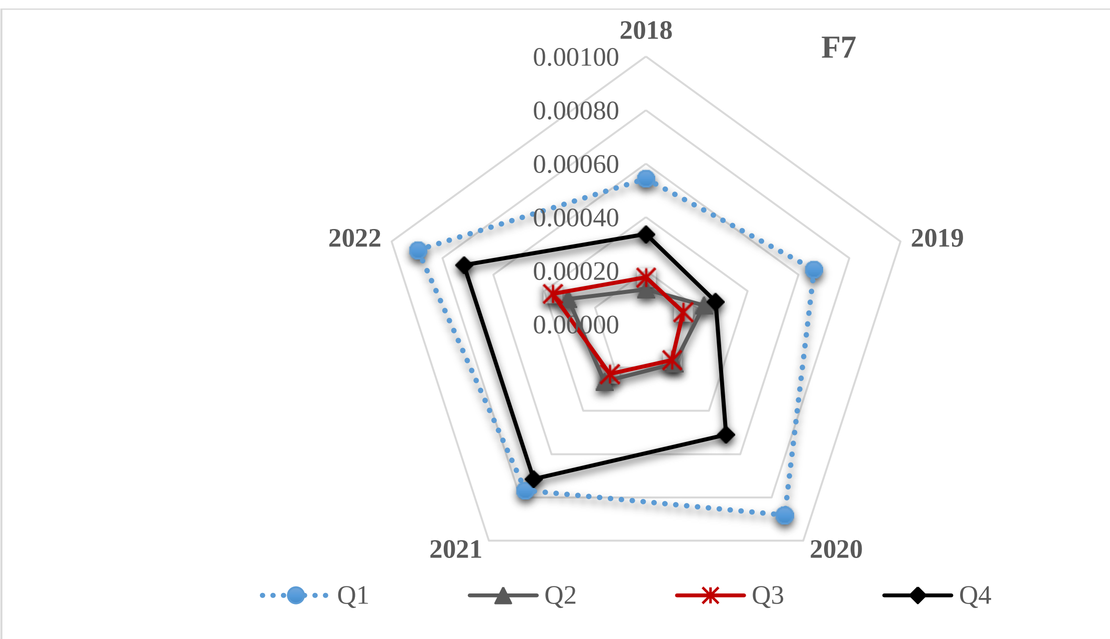


F5 (b)



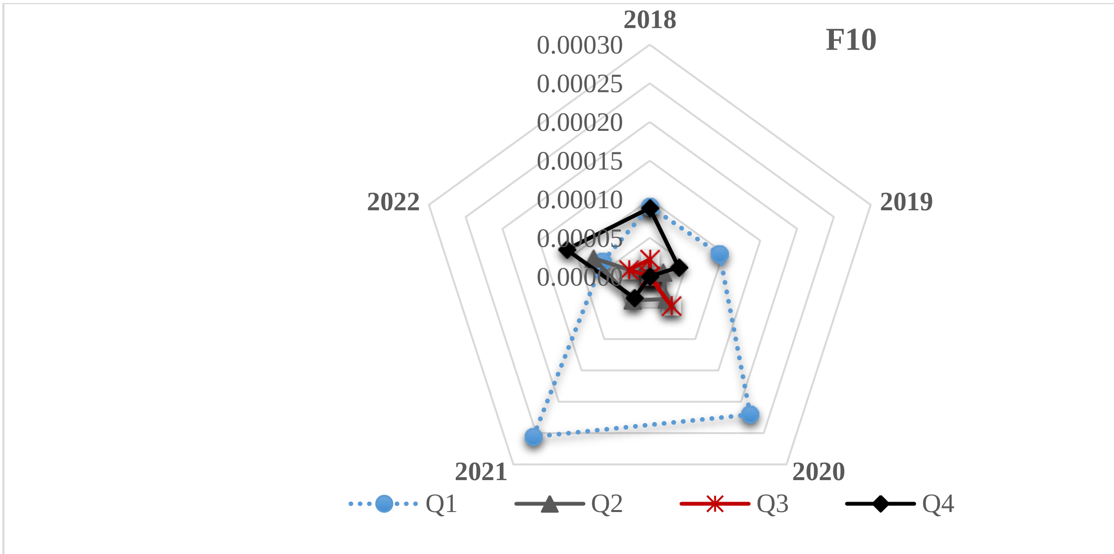
F5
2018
2019
2020
2021
2022
0.00016
0.00014
0.00012
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
Q1
Q2
Q3
Q4

F7 (c)



F7
2018
2019
2020
2021
2022
0.00100
0.00080
0.00060
0.00040
0.00020
0.00000
Q1
Q2
Q3
Q4

F10 (d)



4.10 Cities which have the highest rate of accident

Table 7. *Bronx, Brooklyn. Manhattan. Queens and Staten Island accidents between 2018 and 2022*

Years	BRONX	BROOKLYN	MANHATTAN	QUEENS	STATEN ISLAND
2018	1393	2697	1737	1952	180
2019	1349	2697	1540	1979	212
2020	976	1723	866	1245	124
2021	1076	1856	1088	1286	111
2022	702	1373	825	957	114
TOTAL	**5496**	**10346**	**6056**	**7419**	**741**

Looking at this table data, from 2018 to 2022, the boroughs of Brooklyn, Queens, Manhattan, and Staten Island in New York City experienced varying levels of traffic accidents. Brooklyn had the highest number of accidents each year, with a total of 10,346 accidents over the five-year period. Queens had the second-highest number of accidents, with 7,419 accidents.

On the other hand, Staten Island had the lowest number of accidents each year, with a total of 741 accidents over the five-year period. Manhattan had the lowest number of accidents in 2020, with only 866 accidents, while the Bronx had the lowest number of accidents in 2022, with only 702 accidents.

Overall, the number of accidents seems to have decreased from 2019 to 2020, possibly due to the COVID-19 pandemic and reduced traffic on the roads. However, the number of accidents has increased in 2021 and 2022, indicating a need for continued efforts to improve road safety in New York City.

Figure 14

NY cities' Accidents in 2018 until 2022

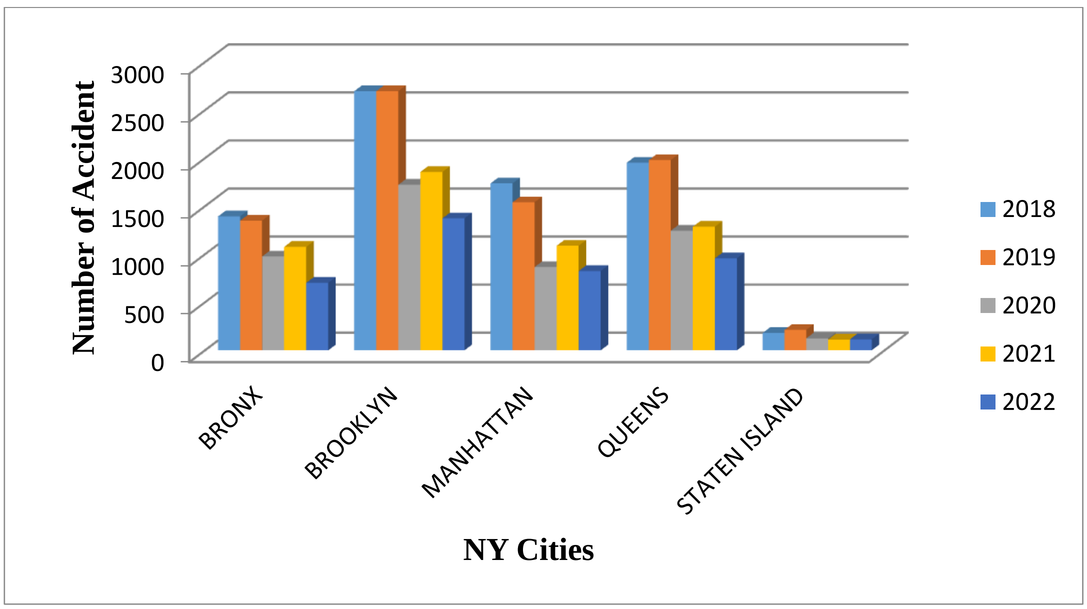


Table 8.

Bronx, Brooklyn, Manhattan Queens, and Staten Island, accidents % in 2018-2022

YEARS	BRONX %	BROOKLYN%	MANHATTAN%	QUEENS %	STATEN ISLAND%
2018	25.35%	26.07%	28.68%	26.31%	24.29%
2019	24.54%	26.07%	25.42%	26.67%	28.61%
2020	17.75%	16.65%	14.29%	16.78%	16.73%
2021	19.57%	17.93%	17.96%	17.33	14.97%
2022	12.77%	13.27%	13.62%	12.89%	15.38%
TOTAL	**100%**	**100%**	**100%**	**100%**	**100%**

CHAPTER V

DISCUSSION

5.0 Introduction

The COVID-19 pandemic has brought unprecedented changes to every aspect of human life, and transportation is no exception. With lockdowns and stay-at-home orders, the number of vehicles and pedestrians on the road has decreased, leading to a significant shift in traffic patterns and accident rates. As a result, researchers and policy-makers are keenly interested in understanding the impact of the pandemic on transportation and traffic safety.

To gain insights into these issues, this study examined pedestrian accidents in New York City over a four-year period, from 2018 to 2022. The study uncovered several noteworthy trends: there were differences in the number and severity of accidents between years, and the pandemic appeared to play a significant role in shaping these patterns. In particular, the researchers found that the pandemic-related changes in traffic volumes and driver behavior resulted in fewer accidents overall, but a higher proportion of severe accidents.

The study sheds light on the complex interplay between the pandemic, transportation, and traffic safety. It also highlights the need for continued monitoring and analysis of these issues, as we navigate the ongoing effects of COVID-19 on our communities and daily lives.

The number of crashes decreased from 10,811 in 2018 to 10,297 in 2019, representing a 4.75% decrease. However, it is still a high number of crashes, indicating the need for continuous efforts to improve road safety, and the number of fatalities increased from 246 in 2018 to 266 in 2019, representing an 8.13% increase. This is a concerning trend, and it highlights the need for more effective measures to reduce fatalities on the roads. Finally, the total number of casualties (fatalities and injuries combined) decreased from 22,986 in 2018 to 21,980 in 2019, representing a 4.38% decrease. While this is a positive development, the number of casualties is still quite high, and there is a need for continued efforts to reduce these numbers.

In terms of injuries, there has been a general downward trend, with the highest number of injuries in 2018 and the lowest in 2020. The injury percentage has also been decreasing, with the highest percentage of 22.03% in 2018 and the lowest percentage of 13.47% in 2020.

The number of casualties has been decreasing over the years, with a significant drop from 2018 to 2020. However, there was a slight increase in 2021 and a significant increase in 2022.

Overall, it appears that there has been a positive trend in terms of the number of accidents and injuries. However, the fatality percentage and the number of casualties have not been consistent over the years, indicating that there may be other factors at play that need to be considered. It would be helpful to analyze the data further to identify any underlying causes or patterns that could help inform strategies to reduce the number of accidents and fatalities in the future.

CHAPTER VII

CONCLUSION AND RECOMMENDATION

Conclusion

In conclusion, this study analyzed the number of accidents and casualties in New York City over period of five years, divided into pre-COVID-19, COVID-19, and post-COVID-19 periods. The study found that in 2018, 10,811 accidents led to fatalities 21.57% and 26.65% injuries. In 2019, the accident decrease, but a rise in fatalities 23.33% even though injuries decreased to 25.45%. The year 2020 marked a significant drop in accidents to 6,540 and fatalities 18.42%, along with a sizable decrease in injuries to 16.3%. In contrast, 2021 witnessed an increase in accidents to 7,324 and fatalities 23.15%, and an increase in injuries to 18.19%. The 3-D plot of the number of accidents versus the month and time block showed that the pattern of accident occurrence in NYC with respect to the period and time of occurrence did not significantly change.

The study further revealed that the lockdowns and subsequent reopening had a significant impact on the number of accidents and casualties in NYC. For instance, the first lockdown, which started in March 2020, resulted in a significant trough in the number of casualties and accidents. However, with the first phase of reopening in June 2020, the number of accidents and casualties increased significantly. This trend continued with the second phase of reopening, which allowed up to 150 socially-distanced graduations.

Additionally, the study identified that the accident indices were higher between 18:00 to 6:00, and the severity of accidents during this period was higher than those that occurred within12:00-17:59. The research further provides a comprehensive analysis of the factors contributing to accidents resulting in injuries and fatalities for pedestrians, in the pre-COVID-19, COVID-19 lockdown, and post-COVID-19 years. The results indicate that driver behavior was the leading factor contributing to accidents across all three road user categories. In particular, accidents involving pedestrians and cyclists mostly occurred between 12:00 pm and 11:59 pm. The severity of accidents involving all road user categories increased during the peak COVID-19 pandemic and lockdown period. This study highlights the importance of policymakers considering the potential consequences of their decisions on public health and safety before implementing measures such as lockdowns and reopenings. By examining the impact of such measures on accidents and casualties, this study provides valuable insights that can inform evidence-based road safety policies and interventions aimed at reducing the number of accidents resulting in injuries and fatalities for all road users. These insights can be used to inform policy decisions aimed at promoting public safety. Overall, this study underscores the need for policymakers to prioritize public health and safety when making decisions that impact the wider community.

Recommendation

- Pedestrian education and training: The pandemic has brought about changes in people's routines and habits. Increased pedestrian activity in certain areas or times might increase the risk of accidents. Safety training and awareness campaigns, particularly focused on changes brought by the pandemic, could be beneficial.
- Infrastructure improvement: The shift in pedestrian and vehicular traffic patterns during the pandemic could highlight areas where infrastructure changes could improve safety. This could include improved crosswalks, traffic calming measures, and better lighting.
- Incorporation of new mobility patterns: Remote working and learning have led to changes in peak traffic times and locations. These changes should be considered in traffic management and urban planning.
- Increased enforcement of traffic rules: During the pandemic, fewer cars on the road may have led to more speeding, which is associated with increased accident severity. Enforcement of speed limits should be increased, with a particular focus on times and places where pedestrian activity is high.
- Further research should be conducted to obtain a larger accident analysis in order to increase the generalizability of the findings.

- Better public transportation: Reducing the number of cars on the road is a proven way to decrease pedestrian accidents. Improvements to public transportation, in terms of both coverage and safety in a post-COVID-19 world, can help in this regard.
- Data Collection and Analysis: Regular monitoring and evaluation of the accident data can help in identifying problem areas and devising targeted interventions. Special attention should be given to understanding how the pandemic has changed these patterns.
- Health Promotion: Many individuals have turned to walking as a form of exercise during the pandemic. Efforts should be made to promote this trend, but in a safe way. This could include creating pedestrian-only zones or times, and promoting safe walking practices.
- Legislation and Policy: Policies related to pedestrian safety should be reviewed and updated considering the changes brought by the pandemic. This could include policies related to speed limits, pedestrian rights, infrastructure design, etc.

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APPENDICES A

Accident Number, Fatality, injury, Casualty, Severity Index, fatality index and causality index in 2018

2018							
Accident Date	**Sum of Accident Number**	**Fatality**	**Injury**	**Causality**	**Severity index**	**Fatality index**	**Causality index**
Jan	991	14	2060	2074	0.006	0.014	2.092
Feb	960	18	1990	2008	0.008	0.018	2.091
Mar	933	22	1956	1978	0.011	0.023	2.120
Apr	720	14	1517	1531	0.009	0.019	2.126
May	862	16	1814	1830	0.008	0.018	2.122
Jun	777	20	1672	1692	0.011	0.025	2.177
Jul	695	18	1482	1500	0.012	0.025	2.158
Aug	704	8	1564	1572	0.005	0.011	2.239
Sep	858	34	1823	1857	0.018	0.039	2.164
Oct	950	14	1976	1990	0.007	0.014	2.094
Nov	1089	30	2262	2292	0.013	0.027	2.104
Dec	1272	38	2624	2662	0.014	0.029	2.092
TOTAL	**10811**	**246**	**22740**	**22986**	**0.0107**	**0.022**	**2.1261**

Accident Number, Fatality, injury Casualty, Severity Index, fatality index and causality index in 2019

Accident Date	**Sum of Accident Number**	**Fatality**	**Injury**	**Causality**	**Severity index**	**Fatality index**	**Causality index**
Jan	1011	22	2106	2128	0.0103	0.0217	2.1048
Feb	811	20	1716	1736	0.0115	0.0246	2.1405
Mar	833	20	1748	1768	0.0113	0.0240	2.1224
Apr	736	16	1544	1560	0.0102	0.0217	2.1195
May	885	22	1846	1868	0.0117	0.0248	2.1107
Jun	719	18	1548	1566	0.0114	0.0250	2.1780
Jul	676	18	1462	1480	0.0121	0.0266	2.1893
Aug	709	26	1486	1512	0.0171	0.0366	2.1325
Sep	798	20	1724	1744	0.0114	0.0250	2.1854
Oct	920	22	1958	1980	0.0111	0.0239	2.1521
Nov	923	22	1948	1970	0.0111	0.0238	2.1343
Dec	1276	40	2628	2668	0.0149	0.0313	2.0909
TOTAL	**10297**	**266**	**21714**	**21980**	**0.0121**	**0.0258**	**2.1346**

APPENDICES B

Accident Number, Fatality, injury Casualty, Severity Index, fatality index and causality index in 2020

Accident Date	Sum of Accident Number	Fatality	Injury	Causality	Severity index	Fatality index	Causality index
Jan	862	24	1800	1824	0.01315	0.02784	2.11600
Feb	817	22	1712	1734	0.01268	0.02692	2.12239
Mar	552	12	1152	1164	0.01030	0.02173	2.10869
Apr	148	2	306	308	0.00649	0.01351	2.08101
May	279	6	628	634	0.00946	0.02150	2.272401
Jun	418	22	910	932	0.02360	0.05263	2.22966
Jul	509	16	1150	1166	0.01372	0.03145	2.29076
Aug	497	14	1078	1092	0.01282	0.02816	2.19718
Sep	581	30	1250	1280	0.02343	0.05163	2.20309
Oct	662	26	1366	1392	0.01867	0.03927	2.10271
Nov	635	28	1324	1352	0.02071	0.04409	2.12913
Dec	580	8	1232	1240	0.00645	0.01379	2.13793
Total	**6540**	**210**	**13908**	**14118**	**0.01487**	**0.03211**	**2.15871**

Accident Number, Fatality, injury Casualty, Severity Index, fatality index and causality index in 2021

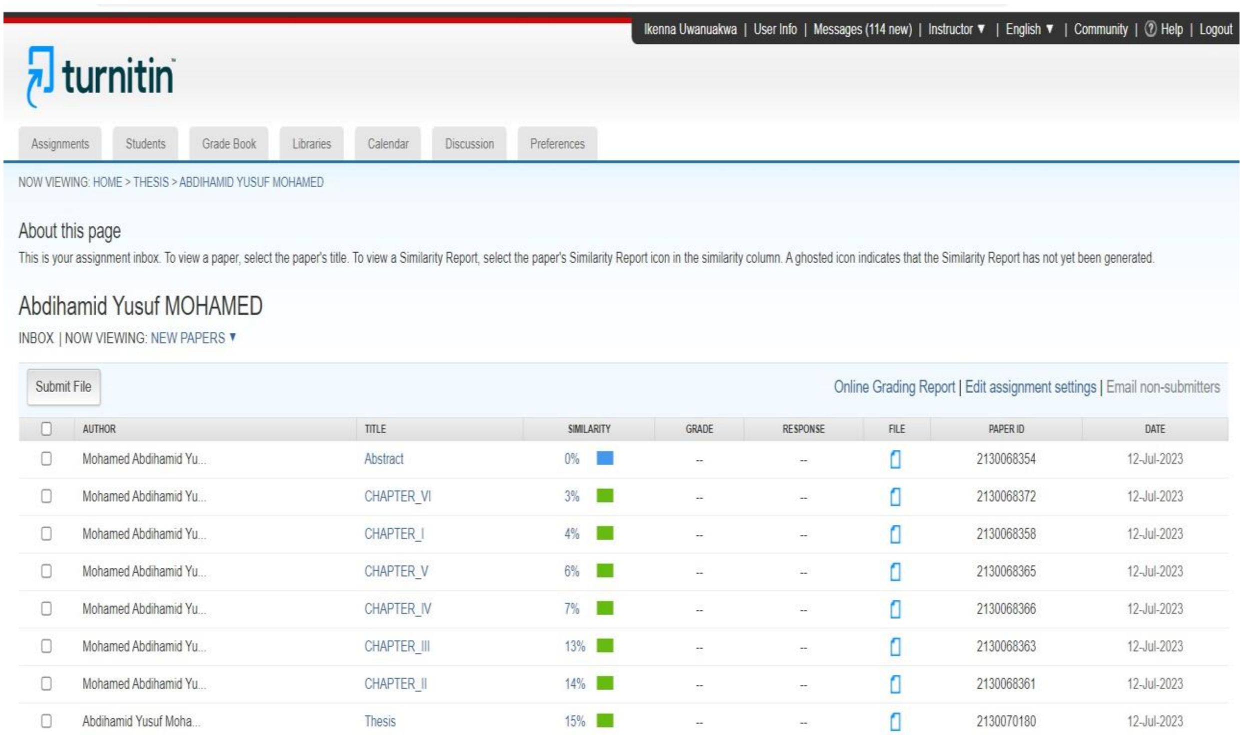
Accident Date	Sum of Accident Number	Fatality	Injury	Causality	Severity index	Fatality index	Causality index
Jan	516	18	1098	1116	0.01612	0.03488	2.16279
Feb	386	18	800	818	0.02200	0.04663	2.11917
Mar	522	20	1098	1118	0.01788	0.03831	2.14176
Apr	539	32	1135	1167	0.02742	0.05936	2.16512
May	636	34	1343	1377	0.02469	0.05345	2.16509
Jun	608	12	1340	1352	0.00887	0.01973	2.22361
Jul	554	18	1179	1197	0.01503	0.03249	2.16064
Aug	570	24	1206	1230	0.01951	0.04210	2.15789
Sep	692	16	1467	1483	0.01078	0.02312	2.14306
Oct	787	30	1662	1692	0.017730	0.03811	2.14993
Nov	752	22	1566	1588	0.013853	0.02929	2.11170
Dec	762	20	1624	1644	0.01216	0.02629	2.15748
Total	**7324**	**264**	**15518**	**15782**	**0.01672**	**0.03604**	**2.15483**

Accident Number, Fatality, injury Casualty, Severity Index, fatality index and causality index in 2022

Accident Date	Sum of Accident Number	Fatality	Injury	Causality	Severity index	Fatality index	Causality index
Jan	658	22	1372	1394	0.01578	0.03343	2.11854
Feb	707	22	1475	1497	0.01469	0.03111	2.11739
Mar	748	16	1566	1582	0.01011	0.02139	2.11497
Apr	652	12	1384	1396	0.00859	0.01840	2.14110
May	659	24	1405	1429	0.01679	0.03641	2.16843
Jun	625	14	1377	1391	0.01006	0.0224	2.22569
Jul	629	24	1396	1420	0.01690	0.03815	2.25755
Aug	604	14	1323	1337	0.01047	0.02317	2.21353
Sep	43	4	89	93	0.04301	0.09302	2.16279
Oct	12	2	24	26	0.07692	0.16666	2.16666
Nov	7	0	14	14	0	0	2
Total	**5344**	**154**	**11425**	**11579**	**0.01329**	**0.02881**	**2.16672**

APPENDICES C

TURNITIN SIMILARITY REPORT



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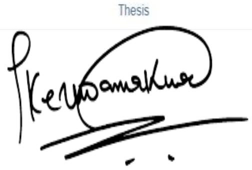

NEAR EAST UNIVERSITY

SCIENTIFIC RESEARCH ETHICS COMMITTEE

25.07.2023

Dear Abdihamid Yusuf Mohamed

Your project **"Effect Of Covid-19 On The Pedestrian Accident Severity: A Case Study New York City"** has been evaluated. Since only secondary data will be used the project does not need to go through the ethics committee. You can start your research on the condition that you will useonly secondary data.

Prof. Dr. Aşkın KİRAZ

The Coordinator of the Scientific Research Ethics Committee

APPENDICES E

Supervisor Certification Letter of Graduation

YAKIN DOĞU ÜNİVERSİTESİ **NEAR EAST UNIVERSITY**

Supervisor Certification Letter of Graduation

July 03, 2023

Ref: 20215603 ABDIHAMID YUSUF MOHAMED

I write to confirm that the aforementioned has completed all the requirements for the award of MSc in Civil Engineering having;

1. Completed 7 courses with minimum grade of CC.
2. Obtained a Satisfactory grade in Seminar.
3. Obtained a Satisfactory grade in Thesis.
4. Obtained a CGPA above 3.00.

Feel free to contact me if you like any further clarification.

Best regards,

Ikenna D. Uwanuakwa, PhD Department of Civil EngineeringNear East University, Nicosia TRNC, Mersin 10- Turkey

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