A NEGATIVE BINOMIAL REGRESSION ANALYSIS OF ROAD TRAFFIC DEATHS IN NAIROBI

By

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MASTER OF SCIENCE IN DATA ANALYTICS

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JANUARY ,2025

DECLARATION

I declare that this dissertation is my original work and has never been previously published or submitted elsewhere for the award of a degree. I also declare that this contains no material written or published by other people except where due reference is made and the author duly acknowledged.

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Sign  Date: January 15th, 2024

I do hereby confirm that I have examined the master's dissertation of

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ABSTRACT

The majority of people in Kenya travel by road, with a sizable portion of the population relying on various modes of transportation for daily commuting. Road Traffic accidents (RTAs), also known as collisions or crashes, happen when a car hits another car, a pedestrian, a road barricade, an animal, or any stationary object like a tree or electricity pole. (RTAs) are becoming common in Kenya and other African countries due to population growth and increased motorization. There are significant barriers to road safety in Kenya, as highlighted by the 2023 economic survey, which revealed an astounding 4,690 fatalities on Kenyan roads in 2022. The proposed study's goal was to analyze Road Traffic Deaths in Nairobi using a Negative Binomial Regression Model. The model was validated using the Pearson Chi-Squared Statistics and the root mean square error. Majority of studies that have been conducted have analyzed the effects of weather parameters, road structure, and environment on traffic accidents; however, human factors like gender, age, and drug use are frequently interrelated when determining the death rate of an accident. The data used in the study was secondary between the period of 2017- 2023, derived from Traffic base commanders in Nairobi County, and National Transport Safety Authority (NTSA) accident data. The analysis revealed a decline in road fatalities from 2020 to 2023. The study found that drivers were responsible for the majority of fatal road accidents, with most occurring on Saturdays and Sundays. The cause of death coefficients were as follows: drivers (0.3645), pedestrians (0.4439), pedal cyclists (0.4914), and vehicle defects (0.5871). The study's findings are expected to contribute to enhanced road safety measures, guiding the development of better policies, rules, and interventions aimed at reducing the death toll and its adverse effects on Kenya's economy and society.

Keywords: Road Traffic Accidents, Negative Binomial Model, National Transport Safety Authority, Road Traffic Death

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ACRONYMS AND ABBREVIATIONS

ANN	Artificial Neural Network
CPM	Crash Predictive Model
DT	Decision Tree
ECMT	European Conference of Ministers for Transport
KeNNHA	Kenya National Highway Authority
KeRRA	Kenya Rural Roads Authority
KRB	Kenya Roads Board
KURA	Kenya Urban Roads Authority
NBR	Negative Binomial Regression
NTSA	National Transport and Safety Authority
OECD	The Organization for Economic Cooperation and Development
PSV	Public Service Vehicles
RF	Random Forest
RF	Random Forest
RF- BO	Random Forest Bayesian Optimization
RTA	Road Traffic Accidents
RTD	Road Traffic Death
RTI	Road Traffic Injuries
SGG	Sustainable Development Goals
SVM	Super Vector Machine
WHO	Word Health Organization
XG BOOST	Extreme Gradient Boost
ZTNB	Zero Truncated Negative Binomial
ZTP	Zero Truncated Poisson Model

CHAPTER ONE: INTRODUCTION

1.0 Introduction

The objective of the study is to apply and evaluate the Negative Binomial Regression-model and analyze factors related to deaths from Road Traffic Injuries. The chapter provides an overview of the study, including its context, problem statement, justification, research questions, scope, and limitations.

1.1 Background of the study

A Road Traffic Accident is an incident involving at least one moving road vehicle on either a public or private road accessible to the public, leading to the injury or fatality of at least one individual (United Nations, European Union, and the International Transport Forum at the OECD, 2019). Research indicates that inexperienced drivers, malfunctioning vehicles, carrying an excessive number of passengers, breaking traffic laws, damaged roads, and a lack of footpaths are the main causes of (RTAs) (Islam et al., 2020).

As per the (World Health Organization,2023), roughly 1.19 million individuals succumb annually due to RTAs. These accidents constitute the primary cause of death among children and young adults aged 5–29 years. According to the 2018 World Health Organization (WHO) study, there is a notable disparity between the death rate per 100,000 inhabitants and the ratio of registered vehicles per 1,000 individuals in the African region when compared to the worldwide perspective.

The severity of road traffic deaths (RTDs) on vulnerable road users, such as cyclists, pedestrians and motorbike riders along with their passengers, has been extensively investigated in both historical and current studies (Muguro et al., 2020). These investigations have consistently highlighted the significant impact of RTDs on these groups, accounting for a substantial 46% of global traffic fatalities (World Health Organization, 2018) as depicted in Figure 1.

FIGURE 1

Fatalities by User Comparison Chart

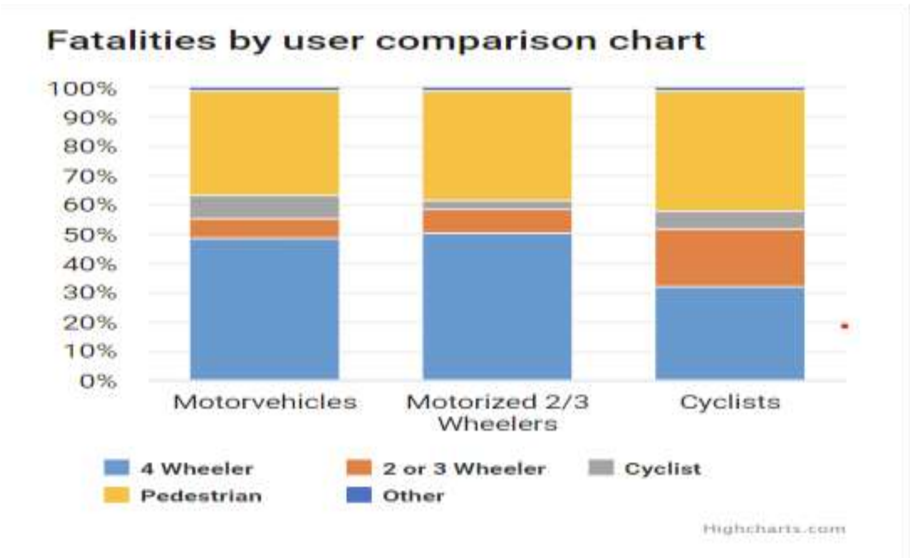

Figure 1:Data Visualization of Road Traffic Accidents

(Source: WHO https://extranet.who.int/roadsafety/death-on-the-roads/#alcohol)

Despite having the lowest rate of motorization and the smallest network of roads, Africa faces the highest death rate among all continents, highlighting a pressing road safety concern. This issue is exemplified in case studies across the continent, such as the one in Nigeria where road traffic crashes are a major public health challenge (Oluwadiya et al., 2019). These challenges have prompted Africa to commit to enhancing road safety outcomes through various initiatives, including the Sustainable Development Goals (SDGs), the African Road Safety Action Plan, the African Road Safety Charter, and the Global Plan for the Decade of Action (2011-2020).

In examining the severity of the problem, a study by (Ezenwa et al., 2018) highlights the need for comprehensive interventions 2017, the World Health Organization advocated for the adoption of 12 voluntary global performance targets regarding the implementation of key UN vehicle safety regulations in G20 nations (World Health Organization, 2023). The implementation status of these regulations, such as the UN 1958/1998 Agreements, New Car Assessment Programme, and various safety standards like frontal impact, side impact, seatbelt anchorages, pedestrian protection, ESC (Electronic Stability Control), child seats, and others, was examined in major G20 countries. The regulations, approved by the UN General Assembly in April 2018, serve as a global framework of safety performance indicators aimed at reducing road deaths and serious injuries.

To oversee the development, management, maintenance, and restoration of road infrastructure management the Kenya Rural Roads Authority (KeRRA) and the Kenya National Highways Authority (KeNHA), Kenya Urban Roads Authority (KURA) were established by the Roads Act of 2007. Kenya Roads Board (KRB) invites applications and allocates cash for the improvement of the transportation system whereas the Nairobi Traffic Department's and the City Inspectorate Department's enforcement responsibilities are to guarantee adherence to County Government and Traffic Act rules. The goal of the Transport and Safety Authority (NTSA) is to create a sustainable, safe road transportation system in an attempt to lower road accidents, the Authority is in charge of licensing, registration, and traffic safety (Housing, Urban Development & Public Works, State Department for Infrastructure, 2022). This shows the government's efforts to mitigate the impacts of (RTAs), which support the development of a solid policy formulation framework.

According to the NTSA-Road-safety-reduction-in-fatalities-status-update published on March 23, 2023, there has been a 4.6% decrease in fatalities, with the number dropping from 1,021 to 974 in comparison to the corresponding period in 2022 (NTSA, 2023). The aforementioned decrease highlights the success of ongoing road safety initiatives in mitigating the occurrence of fatalities on roadways, as evidenced by a notable decline in fatalities among pedestrians, motorcyclists, and passengers riding on the back of motorcycles.

In Kenya, the primary entity overseeing road safety initiatives is the National Transport and Safety Authority (NTSA), situated within the Ministry of Transport, Infrastructure, Housing, and Urban Development. This agency receives financial support from the national budget. The NTSA is tasked with multifaceted responsibilities, Involving the coordination, enactment of laws, and oversight and assessment of road safety strategies. (Negussie et al., 2018). The Kenyan government through the Traffic Act Cap put in place measures to reduce road traffic accidents, through the government road safety mainstreaming program and usalama barabarani initiatives as shown in the table below.

TABLE 1

Table showing the Summary of Fatalities as of March 2023

Details	2022	2023	variance
Pedestrians	330	359	-8.078
Drivers	98	95	3.158
Passengers	171	154	11.04
Pillion passengers	93	109	-14.68
Pedal Cyclists	17	15	13.33
Motor Cyclists	265	289	-8.304
Total	974	1021	-4.6

Table 1:Summary of Road Traffic Deaths as of March 2023

Source: https://www.ntsa.go.ke/

In the context of developing and developed nations, Kenya's road network, totaling approximately 2,979 kilometers, has grown gradually but remains insufficient. Of this network, only around 38 percent (1,100 kilometers) is paved, 600 kilometers are gravel, and about 42 percent (1,270 kilometers) consists of unpaved earth roads. This deficiency, coupled with aging drainage systems, has led to ongoing challenges such as flash floods, rendering public road transportation less effective. Despite recent infrastructure advancements, road fatalities persist, prompting the implementation of various measures by the Kenyan Transportation Authorities.

Public Service Vehicles (PSVs) are key in meeting the transportation needs of a diverse population in Kenya (Muguro et al., 2020). However, safety concerns associated with the Matatu industry have been identified PSV's.In the country are permitted to carry anywhere from 10 to 50 people, based on the vehicle type (Republic of Kenya [GoK], 2018), often utilized for ferrying individuals between locations.

The prevalence of road accidents in Kenya, resulting in a significant toll of deaths and injuries, poses a major challenge to the country's social fabric and economic growth. Notable measures, such as prohibiting the operation of PSVs at night until they conform to governmental standards, have been implemented. However, dissent from those involved in public transportation suggests a disregard for their concerns. Efforts to reduce traffic accidents face challenges as transportation authorities and PSV drivers persist in attributing faults to each other.

Concerns have also been raised about the effectiveness of traffic police in preventing accidents, with corruption cited as a major factor hindering their ability to enforce regulations. The National Transportation and Safety Authority (NTSA) has taken significant steps to address this issue, with a focus on developing a safe and sustainable road network. This commitment reflects the government's recognition of the importance of research in mitigating the negative impacts of (RTAs) informing effective policymaking.

In Kenya, (RTAs) contribute to nearly three thousand annual fatalities and disabilities due to transport-related incidents. Despite continuous efforts to improve road infrastructure and safety features, accidents persist at an alarming rate, incurring significant economic costs and giving rise to social and economic issues. According to the (WHO) 2018 worldwide status report on road safety, there has been a discernible rise in the death tolls associated with RTAs, particularly affecting low-income and middle-income nations, accounting for over 93% of incidents. Notably, road traffic deaths are a primary contributor to mortality Within the demographic ranging from 5 to 29 years old, and injuries and fatalities exceeding 50% affect individuals within the economically active age bracket of 15 to 49 years (Chen et al., 2019).

Concerns about the accuracy of recorded numbers have been raised, with discrepancies attributed to data collection and classification practices. The National Transportation and Safety Authority (NTSA) reporting fatalities based on a dead-on-the-spot approach, without a 30-day follow-up with hospitals, deviates from international standards (World Health Organization [WHO], 2018). These issues show the multifaceted challenges in addressing road traffic accidents and the importance of comprehensive and accurate data for effective policymaking and intervention strategies.

1.2 Statement of the problem

The existing literature extensively examines the frequency and severity of traffic accidents, employing traditional statistical methods such as linear and non-linear regression analyses (Wahab et al., 2019). While machine learning techniques have been explored to assess these methods' advantages and drawbacks, recent studies have highlighted limitations in linear regression models, prompting the search for more suitable alternatives (Naqvi et al., 2021). Notably, the negative binomial model emerges as a preferable choice for data characterized by gamma distributions, especially in cases where missing values pose challenges.

Despite efforts by the Kenyan Government through the Ministry of Transport in collaboration with state parastatals mandated to ensure the development of good quality roads, NTSA and the Kenya Traffic Police putting in place measures to increase the safety of roads and prevent accidents (RTAs) remain the main cause of Deaths in Kenya (Muguro, Sasaki, Matsushita, & Njeri, 2020). According to (Tavakkoli et al., 2022) Only 6 of the 236 research on traffic accidents that were included in 13 Cochrane reviews were carried out in low- and middle-income countries. The study further highlighted that most research does not focus on the impact of vulnerable road users in the study (pedestrians and motorcyclists). The lack of comprehensive research focusing on vulnerable road users, such as pedestrians and motorcyclists, highlights an important research gap. Moreover, the inadequacy of preserving data on traffic accidents compromises the effectiveness of preventative measures.

The increasing prevalence of road accidents in Kenya raises significant concern, yet the limited number of studies investigating their underlying causes is troubling (Muguro et al., 2022). Medical experts highlight dissatisfaction with the nation's inadequate preservation of traffic accident data, asserting that these gaps undermine the effectiveness of preventive measures. Government figures released by spokesperson Cyrus Oguna in 2021 indicate a rise in fatalities compared to the previous year, with concerns over incomplete and unreliable injury statistics due to a lack of follow-up data on individuals transported to hospitals (Arsen, 2022; Azevedo & Azevedo, 2017).

1.3 General Objective

i. To analyze Road Accident Data to identify all the direct and indirect causes that have a significant impact on Road Traffic Deaths.

1.4 Specific Objectives

i. To establish the factors influencing road traffic deaths in Nairobi
ii. To develop a Negative Binomial Regression to predict the rate of Road Traffic Deaths in Nairobi
iii. To test and validate the developed model

1.5 Research Questions

i. What are the key factors attributing to the high incidence of road traffic Accidents in Nairobi, and how have these factors evolved?
ii. How do factors influencing (RTAs) contribute to the occurrence of severe Road Traffic Accidents in Nairobi County?
iii. To which extent is the Road Traffic Death Predictive Model accurate and reliable?

1.6 Significance of the study

In Kenya, a lot of people die in road accidents, and many studies have been done on this issue. However, very few studies and Crash Prediction Models focus on how many people die resulting from these accidents. There is no central Road Traffic Accident Surveillance system in place. This study is important because it can help us better what's happening with road accidents in Kenya. By using a special model called the Negative Binomial model, the study aims to look at past trends, find patterns, and predict future accidents. This information can be used to make better rules and safety measures can improve, lowering the death toll and its negative effects on the economy and society. The study could be really helpful for the Kenyan government, transportation agencies, and organizations trying to make the roads safer.

The Proposed study will benefit multiple stakeholders. Civil engineers can enhance road infrastructure design for safer transportation based on identified accident patterns. Policymakers can use the insight from the study to formulate evidence-based regulations and interventions to reduce accidents and fatalities, contributing to improved road safety. The general public stands to gain from the study's focus on decreasing accident risks and improving the Roady safety measures for pedestrians, cyclists, and motorists.

1.7 Motivation of the study

Road Traffic Injuries (RTI) are the leading cause of death worldwide, accounting for around 1.3 million deaths annually (WHO, 2018). Data on road safety are typically temporally connected and frequently take the form of counts. Count Data analysis is considered when analyzing outcomes that estimate covariate effects of the outcome (Zhenge et al., 2021). While various empirical equations have been created for accident predictive models, there have been opportunities recently to apply novel regression approaches in this field.

Numerous investigations have been conducted to formulate models that depict the connection between the predicted Road Traffic Accident frequency and various factors like traffic flow, geometric attributes, and environmental conditions, utilizing both static and dynamic methodologies. However, the fixed parameters in all the aforementioned studies overlook the potential variability in the impacts of risk factors among different observations (Mylonas et al., 2023).

1.8 Scope and Limitations of the Study

In Kenya, efforts to develop a Road Traffic Accident surveillance system are being limited and low. Numerous variables, which may potentially be observed but likely at a significant expense, include factors like previous and current road safety policies, driving under the influence regulations, road users' familiarity with rules and regulations, car quality, and road quality. The absence of standardization of terms between various databases, (e.g., due to disparities between the NTSA, health sector and police records), additionally restricts the capacity to compare data. For example, when defining road traffic death, different criteria are used to determine the allowable period between a crash and the occurrence of death. Only fatalities that occur immediately are included in the death count in certain nations.

If a death occurs a year after an accident, it is still classified as a road traffic death in developed countries. Thirty days after an accident is the generally accepted norm. Nevertheless, not all countries follow this standard, mainly because of differences in how much they rely on police or hospital records. To address this problem, the (WHO) employs the ECMT standardized 30-day-road-crash-death adjustment factors, which enable them to standardize and compare road traffic fatalities across different countries using the same criteria. (WHO, 2009).

1.9 Structure of the Research

The subsequent segment incorporates a review of relevant literature within the study. and surveys the suggested methodology. It also includes a thorough explanation of the model's framework that will be used, as well as a timeline and expected resource list.

1.10 Ethical Considerations of the Study

During the study period, paramount importance will be given to safeguarding the data and confidentiality of all research participants. All data and information utilized in the study will be duly acknowledged to prevent plagiarism and uphold academic integrity. Participants will be informed about the voluntary nature of their participation, ensuring their anonymity and confidentiality throughout the research process. Additionally, they will be made aware of any potential risks or harms associated with their involvement in the study, thereby promoting informed decision-making regarding their participation.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

In this part, previous studies on traffic accidents were reviewed, comparable crash predictive models, and a focus on theoretical and empirical work to identify and understand knowledge gaps and contextualize the research while critically assessing the strengths and weaknesses that contributed to the analysis of the Road Traffic Accident.

2.2 Theoretical Review

To mitigate the negative outcomes of road accidents, previous research has analyzed significant internal and external elements linked to the heightened likelihood of deadly road collisions.

2.3 General Overview

(RTA) deaths have had a significant impact on society, the government, dependents, and families. It has also placed pressure on healthcare facilities in funding, bed occupancy, and demand for medical professionals. (Sowada et al., 2019). Although there exists some literature on the relationships between road safety and economic development. (RTAs) are a major source of health problems and a source of concern for health institutions worldwide;

each year, they result in the loss of approximately 1.35 million lives or leave them disabled. With 1.3 million anticipated road traffic injury deaths in 2019, 93% of road traffic injury-related mortality occurred in low- and middle-income countries. This issue is predicted to get worse; by 2030, traffic injuries will be the seventh top cause of death globally (Ahmed et al., 2023).

2.3.1 *Review of global studies on road traffic accidents*

80% of road traffic deaths worldwide take place in middle-income nations, which also account for 90% of daily disability-adjusted life years and 85% of deaths from RTAs. Approximately 3,700 lives are lost daily in Road Traffic Accidents alone (Abegaz & Gebremedhin, 2019). Notably, half of these casualties involve vulnerable road users, namely cyclists, motorcyclists, or pedestrians.

Although the issue of data reliability and underreporting has been regularly acknowledged, previous forecasts of global fatalities conducted by TRL, the World Bank, and others have produced a wide range of estimates (Al-Madani et al 2019). These forecasts have been based on the use of officially published statistics, which are based on police reports. It was necessary to consider a number of factors in order to derive a more precise estimate of the current global fatality situation (on a regional basis) using these values (Kock et al 2018). These factors are listed below. Based on publicly available data, the study calculates that between 750,000 and 880,000 individuals may have perished in traffic accidents in 1999; the bulk of these deaths happened in developing and emerging countries, with roughly half of them taking place in the Asia-Pacific region (Miccio, 2021).

The number of road deaths is predicted to rise further, reaching between 900,000 and 1.1 million by 2010 and between 1.1 and 1.3 million by 2020. After estimating the approximate global and regional costs of accidents, it was discovered that in 1998, the total cost in developing countries would have been roughly US$65 billion, and the estimated global cost might have been in the range of US$520 billion (Hassan et al, 2022). Trend data revealed that although there has been a steady decline in the West since the late 1960s, the overall number of fatalities from traffic accidents in developing countries is still rising. Nonetheless, there is proof that the number of deaths in the developing countries are still rising (Hassan et al, 2022).

The results also indicate that while fatality risk, or the number of deaths per 100,000 people, is highest in a diverse group of nations that includes Thailand, Malaysia, South Africa, and Saudi Arabia, the highest fatality rates, or deaths per 10,000 motor vehicles, occur in African nations, mainly in Ethiopia, Uganda, and Malawi (Car Accidents Injuries: Death Rate per Country, n.d.). It should be emphasized that, in addition to the Middle East, pedestrians are a particularly high-risk group throughout Asia and Africa. In developed nations, car occupant fatalities predominate, and in Latin America and the Caribbean, they are significantly more frequent (Mittal, 2018).

A case study of the United States shows the severity of the issue. In the year 2020, car accidents emerged as a prominent cause of mortality, claiming the lives of around 40,000 individuals. Additionally, 2.1 million people sought emergency medical care in response to traffic accidents during the same period. World Health Organization (World Health Organization, 2023). Road safety is still a pressing global issue despite significant progress. The cumulative impact of these incidents, including medical costs and loss of lives, is substantial, amounting to an estimated $430 billion. This data emphasizes the imperative of concerted efforts to address and mitigate the multifaceted consequences of traffic accidents on both public health and societal well-being (Bellis et al., 2019).

One of the main objectives of Turkey's transport policy, as stated in the government's long-term annual policy documents, is to improve the physical and legal infrastructure for road safety and control. Moreover, Turkey adopted the Road Safety Strategy and Action Plan in 2012 under the UN's Global Plan for the Decade of Action for Road Safety (2011–2020), which states that the high frequency of traffic accidents in the nation, which result in thousands of deaths or serious injuries annually, is a major social and economic problem (Cetin et al., 2018). In high-income countries, car occupants predominate, In contrast, the most vulnerable road users in low-income countries are pedestrians and (motor)cyclists (Heydari et al., 2019).

FIGURE 2

Roads Per Death, Registered Vehicles per 1000 people against Countries

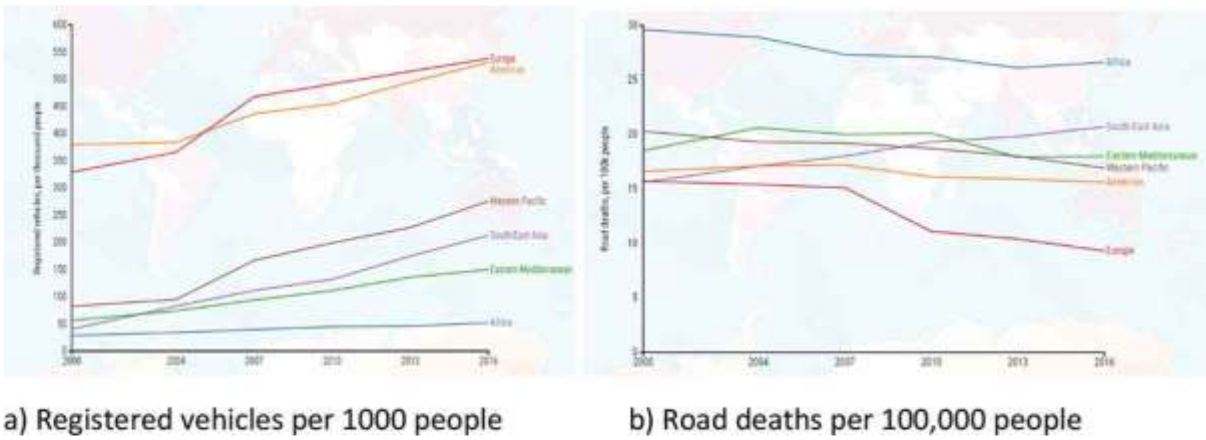

Figure 2: Roads Per Death, Registered Vehicles per 1000 people against Countries

Research indicates that developed countries have the lowest fatality rates (i.e., 1.1 to 5.0 deaths per 10,000 vehicles), while African nations—especially Ethiopia, Lesotho, and Tanzania—have the highest rates (often exceeding 100 deaths) (Al-Madani 2019). A diverse range of nations, including Malaysia, Korea, Latvia, Saudi Arabia, Colombia, and others, had the highest mortality risk (deaths per 100,000 population). As would be expected, most of these analyses show that values in Central and Eastern European nations are more similar to those in Western Europe than they are to those in African, Asian, and Latin American nations (Rodney , 2018).

Countries with high levels of motorization, possessing 60% of the world's vehicles, account for only 14% of global road fatalities. In contrast, the Asia-Pacific region, with just 16% of the world's vehicles, experiences approximately 44% of global road deaths. A similar trend is observed in Central and Eastern Europe, Africa, and the Middle East. Notably, Latin America and the Caribbean are the only regions in the developing world where the proportion of road deaths aligns with their share of global vehicles. (World Health Organization: WHO, 2023). A key distinction between developed and developing regions over the past decade is that road fatalities decreased by approximately 10 percent in Western Europe and North America, whereas they continued to increase across Africa, the Asia-Pacific, and Latin America.

In comparing trends in a relatively small group of countries the changes in the major country can dominate and trends in USA, China, South Africa, Poland, Brazil and Saudi Arabia are shown separately (Baccini, 2023). Notably, the fatality trends in South Africa and Poland stand out compared to other African and Eastern European countries, whereas in other regions, the trends in major and other countries generally follow a relatively similar pattern (Islam, 2021). Between 1987 and 1995, death rates varied significantly across regions. In the Asia-Pacific, deaths rose by 39%, while Africa (excluding South Africa) experienced a 26% increase, and the MENA region saw over a 36% rise. In Latin America and the Caribbean (excluding Brazil), deaths surged by more than 100%. In contrast, Central and Eastern

Europe exhibited mixed trends, with deaths increasing by 31% in Poland but decreasing in other countries. (Bogos et al, 2021).

2.3.2. *Review of regionally studies on road traffic accidents*

In terms of RTA ,the Road Traffic accidents are considered man-made disasters in Ethiopia, where the Ethiopian National Road Safety Assortment Office reports a fatality rate of 114 per 10,000 vehicles annually, although it is acknowledged that the actual figure may be higher due to inaccuracies in the reporting system (Mohammed et al., 2019). Africa has the highest risk of fatalities, with a rate of 24.1 per 100,000 population, and pedestrians accounting for 38% of all road traffic deaths on the continent (Janmohammed, 2018).

In 2008, there were notable percentages of injury-related deaths in Egypt (64%), Tunisia (58%), and Morocco (51%). In addition, there were percentages of 43% in Libya, 42% in Djibouti, 36% in Namibia, and 34% in Niger that were linked to road traffic accidents. The demographic most at risk of road traffic injury-related mortality is the economically active age group (15–59) (Hordofa et al., 2018). Road traffic accidents affect more men than women in this age group (roughly three times as many males as females). In Sub-Saharan Africa, road traffic accidents account for 5% of deaths among males aged 15–59, and 6.5% for males in the 15–29 age group (Demissie, 2017).

According to (Chimba et al., 2017), Human, vehicle, and environmental factors can be integrated into ARIMA and ARIMAX modeling techniques to develop precise predictive models for forecasting crash frequency in Anambra State, Nigeria. The study recommends utilizing these findings to enhance road safety and reduce accident rates across Nigeria.In Nigeria, road traffic accidents are primarily caused by three key factors: human, mechanical, and environmental. Of these, human factors are responsible for over 80% of all traffic crashes

(Adeleke et al, 2020). Specifically, driver-related issues account for approximately 57% of road accidents, with human factors playing a role in 93% of incidents, either alone or in combination with other causes.

These driver-related factors include behaviours, visual and auditory capabilities, decision-making skills, and reaction times (Mohammed, 2019). It is evident that human factors are the most significant contributor to road accidents in Nigeria, which is unsurprising given that people are involved in all aspects of traffic incidents—from poor road design and corrupt law enforcement to careless road use. The same individuals violating traffic laws could be the doctors or nurses responsible for treating accident victims (Adeleke et al, 2020).. Statistical analysis further supports this, indicating that human, vehicle, roadway, and environmental factors collectively contribute to 79.4% of road traffic crashes in the southwestern region of Nigeria. In Côte d'Ivoire, the situation is similarly dire, with human factors responsible for 93.5% of road accidents (Ihueze, 2018).

The primary causes of traffic accidents in Sudan have been linked to driver behaviour, the condition of the vehicle fleet, road infrastructure issues, speeding, failure to use seat belts, and inadequate enforcement of traffic laws (Mohammed et al, 2023). A study on the Khartoum to Medani highway found that the leading contributors to road traffic accidents were improper overtaking (32.3%), pedestrians crossing incorrectly (30.8%), excessive speed (22.6%), and driving under the influence of alcohol (7.5%) (Hammad et al, 2021). Further analysis indicates that 60.6% of road accidents in Sudan were caused by human error, 45.5% by poor road conditions, 5.6% by animals, and 1.4% by faulty vehicles. The ongoing traffic safety challenges in Sudan can largely be traced to a lack of proper monitoring, driver negligence, and deteriorating road conditions (Ali et al, 2022).

Similarly, in South Africa, factors such as drunk driving, road surface quality, and seat belt usage have been identified as key determinants of road-related fatalities (Mpunzi, 2018) . The 2016-2017 report from South Africa's Road Traffic Management Corporation identifies human factors as the leading cause of 77% of fatal road accidents. Road conditions account for 16%, and vehicle-related issues contribute to 6% (Montle & Moleke, 2021). Among the human factors, almost 80% of fatal accidents involved jaywalking (52.5%) and speeding (11.6%). Road and environmental factors were responsible for 12.7% of the accidents, with sharp bends (22.0%) and poor visibility (16.5%) being the primary contributors. Vehicle-related issues caused 7.8% of fatal accidents, with tire blowouts being a factor in 71.7% of these cases (Janmohammed, 2018). Road traffic accidents in South Africa are strongly linked to environmental and human factors, with high-speed driving posing a significant risk, especially among individuals prone to sensation seeking. Additional risk factors include substance abuse—such as alcohol, drugs, and binge drinking—as well as distractions like cell phone use and conditions like attention deficit disorder (with or without hyperactivity) (Verster &Fourie, 2018).

In Botswana, road accident fatalities have been notably higher compared to many other African countries. The primary contributors to these accidents include speeding, driving under the influence of alcohol, and worsening traffic congestion, particularly during peak hours in urban areas (Mphela, 2020). Similarly, in Eswatini, Masuku points out that driving at high speeds, especially during adverse weather or at night when visibility is poor, is a significant factor in road traffic accidents. Additional causes include dangerous and reckless driving, particularly when drivers ignore barrier lines, and alcohol abuse by both drivers and pedestrians. Fatigue has been identified as a leading cause of accidents, especially among public transport drivers (Mapendere, 2020). Vehicle-related issues, such as tire blowouts and defective brakes, also contribute to accidents, while pedestrian negligence—such as walking on freeways—remains a major concern (Gelderbloom, 2021).

2.3.3 *Review of kenyan studies*

The rapid expansion of motorcycle transport, commonly referred to as boda-boda, has grown alongside the established Matatu industry and is becoming increasingly prevalent across the country (Murumba, 2017). According to studies (Diaz Olvera et al., 2019; D. Wang et al., 2019; Soehodho, 2017), there has been an increase in injuries and fatalities among users and pillion passengers as a result of the growing reliance on motorized two- and three-wheeled vehicles. The nationwide increase in registered vehicles makes this issue even worse. As noted by Islam and Al Hadhrami (2012), higher motorization rates correlate with an increase in road traffic accidents.

Public service vehicles (PSVs) are the backbone of the country's transportation system, serving a wide range of commuters. However, Kenya's public transport sector, particularly the matatu industry, has been frequently criticized for its safety standards (Manyara, 2016; Mugambi & Nyakeri, 2015). PSVs in Kenya are legally authorized to carry between 10 and 50 passengers, depending on the vehicle type (Government of Kenya, 2018). Yet, it is common for these vehicles to exceed their passenger limits, often ignoring the regulations for each category (Muguro, 2019). This disregard for capacity limits increases the number of casualties in the event of a traffic accident. Furthermore, PSV drivers are typically paid on a per-trip basis, navigating congested roads that are often unmarked or unsigned, while competing with other motorists on the same routes. This system fosters aggressive driving behaviour and increases the risk of accidents (Osoro, 2024).

In Kenya Nairobi, stands as the hub of the nation's administrative offices and commercial enterprises, serving as the economic center not only for Eastern Africa but the entire Central African region. With remarkable population growth since 2009, Nairobi's population reached 4,397,073 in the 2019 Population and Housing Census, marking a 4.0 percent increase from the previous year (Population and Housing Census, 2019).

The Kenya Traffic Police Department reports that various types of vehicles—including motor cars, lorries, buses, taxis, motorcycles, pedal cycles, animals, and matatus—are the main culprits behind RTAs on Kenyan roads. Of these, 582 incidents involving individuals involved in motorcycle accidents were reported in a high number of incident reports(Ogot et al., 2018.).

(Ogot et al., 2018) state that human factors—drivers (43.6%), pedestrians (24.8%), passengers (4.8%), and pedal-cyclists (10.3%)—are the primary cause of road accidents, accounting for 85.5% of incidents. (Khayesi, 2020) emphasizes that vulnerable road users, including passengers on motorcycles, the elderly, children, and pedestrians, are particularly vulnerable to accidents. The consequences of road traffic accident (RTA) fatalities go beyond the individuals involved; they affect the victims' families, dependents, society, and the government at large (Makuu, 2018). This has resulted in a significant burden on healthcare resources, including funding, bed occupancy, and the demands placed on healthcare professionals.

According to data gathered from the 2023 economic survey, there were 4,690 reported deaths on our roads in 2022, compared to 4,579 in 2021, indicating an increase of 111 fatalities, representing a 2.4 percent rise (Kinyanjui, 2023). These (RTAs) have inflicted significant suffering on numerous families across the country, resulting in orphans, widows, and families losing their main sources of income. Additionally, many individuals have sustained lifelong injuries, serving as constant reminders of their close encounters with death.

According to further information from the National Transport and Safety Authority (NTSA), by October 2023, the nation recorded 3,609 deaths, marking an 8.9 percent decrease compared to the 3,936 fatalities reported during the same period in 2022(Kinyanjui, 2024). This decline is attributed to concerted efforts by various stakeholders to mitigate road accidents. NTSA further approximates that annually, approximately 3,000 Kenyans lose their lives due to road accidents, which incur a cost to the country ranging from 3-5 percent of the Gross Domestic Product (GDP), (Moturi, 2019). A staggering 83 percent of these fatalities are men, predominantly within the age range bracket of 30-34 years, signifying a noteworthy loss of productivity for the nation. However, the World Health Organization (WHO) presents even higher figures. Unfortunately, despite efforts, the statistics from NTSA demonstrate a consistent annual increase in these numbers.

The National Transport and Safety Authority's technical reports suggest that urban planning incorporate road safety as a fundamental element. Numerous interested parties stress the significance of urban traffic planning for traffic law enforcement and road safety(World Health Organization, 2023). By involving all parties involved in road safety in the development of road safety initiatives and programs, this study will close the gap and lessen the number of RTDs in Nairobi County.

2.4 Theoretical framework

Individuals have the capacity to think rationally and make decisions that can either result in accidents or help mitigate their consequences. As noted by (HSE, 1999), efforts to enhance safety have traditionally been reactive in nature, with a predominant focus on investigating accidents after they occur in order to prevent similar incidents in the future. Various theories have been put forward to explain the role of human error as a major contributing factor to accidents, highlighting the importance of understanding these behaviours to improve overall safety.

According to (Asingo, 2007) the need to understand transport networks through an integrated systems approach, where structural and functional linkages play a key role within the greater framework. Because of its connections to so many other economic sectors, the transportation sector is essential to economic growth. In both rural and urban environments, transportation is essential for accessing different locations, industries, and services, including agricultural resources (Osoro, 2024). At a At a more technical level, road transport is a superstructure that is based on two main pillar for road infrastructure and road transport. These pillars share the common goal of ensuring safe and efficient road transport and rely on solid institutional foundations. The effectiveness of road transport is directly tied to the robustness of these these pillars, which are dependent upon how strong their institutional foundations. Additionally, the sustainability and success of these foundations are influenced by the degree of stakeholder involvement as well as involvement in the process of making decisions. Therefore, the efficiency and safety of road transportation systems hinge on maintaining strong, well-connected institutional and structural pillars that promote active engagement across all levels (Economic Review, 1997).

2.4.1 *Sociological theory*

The theory suggests that social groupings possess different cultural traits, such as a unique perspective on the world and certain patterns of behaviour that impact their members. The cultural attributes might result in divergent interpretations of a given circumstance among drivers from various groups (Knoll et al., 2021), thereby leading to opposing actions that may potentially result in road accidents. Drivers are influenced by various factors, such as other road users, societal standards, and traffic legislation, which dictate how they interact while driving.

2.4.2. *Cause Theory*

Accordingly, the accident is not anticipated in reality and may result in unfavourable effects like deaths, injuries, near misses, damaged property, or broken nerves. The main objective behind the creation of accident causation models was to assist those who wanted to investigate word-related mishaps so that they could be effectively investigated (Sharma et al., 2017). Understanding the causes of accidents is also helpful from a preventative standpoint, as it allows one to identify the types of mistakes or disappointments that typically lead to accidents. This allows proactive measures to be taken to remedy these mistakes or disappointments before they have a chance to occur (Awal & Hasegawa, 2017).

2.4.3 *Domino theory*

In 1931, H.W. Heinrich introduced a collection of principles called 'the axioms of industrial safety'. The first principle addresses the cause of accidents by asserting injuries always arise from a complex series of variables, with the accident itself being the final item in this process. In addition, he introduced a concept called the 'domino theory', which compared this succession of accidents to a series of dominoes falling one after another. The chronology is as follows: Injury caused by an accident resulting from a dangerous act or mechanical or substantial hazard, caused by the individual, which is influenced by their social surroundings and lineage. Unsafe activities of individuals account for 88% of all accidents, while unsafe actions contribute to 10% and acts of God are responsible for 2%. Heinrich introduced a concept called the "five-factor accident sequence" in which each element triggers the next stage, similar to a series of dominoes falling one after another (Qalb et al., 2023).

FIGURE 3

Illustration of Domino Theory

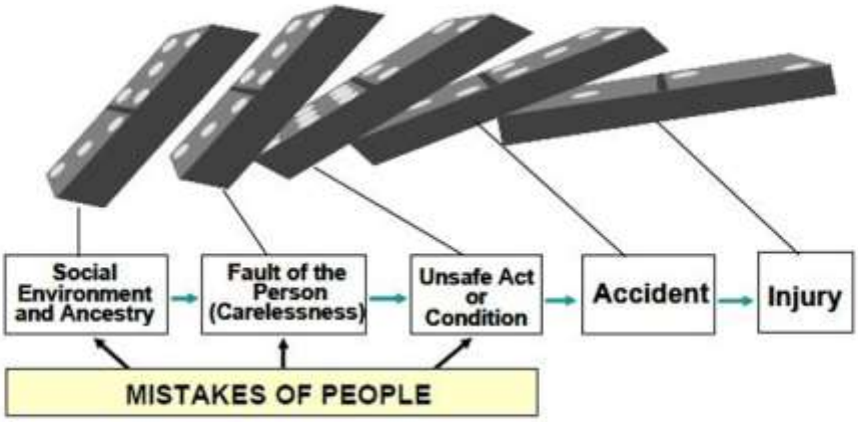

Figure 3: Illustration of Domino Theory

Source: https://www.researchgate.net/figure/Domino-theory-of-accident-causation_fig1_268439084

Peterson (1978) asserts that every collision is accompanied by a multitude of contributing elements, factors, and sub-factors. The multiple relationship hypothesis shows that various elements coalesce in a stochastic manner, resulting in accidents. During accident investigations, it is crucial to uncover as many causes as feasible, rather than attributing only one cause to each stage of the domino sequence.

2.4.4 *Homeostasis theory*

Homeostasis is a dynamic process that maintains the outcome near the desired aim by counteracting disruptive outside factors.Hazard equilibrium refers to the consistent level of risk-taking behavior and the resulting losses from accidents and lifestyle-related diseases that are constant unless it is a deliberate shift desired level of risk. Based on the information provided, it is evident that the causality of accident loss in a nation can be attributed to a homeostatic mechanism.

The individual's perceived degree of traffic accident risk at any given instant is influenced by three factors:

i. The individual's encounter with traffic.
ii. The individual's evaluation of the possibility that an accident will occur in the current circumstances.
iii. Personal level of self-assurance in their ability to effectively navigate the circumstance by making appropriate decisions and skilfully operating the vehicle.

FIGURE 4

The Theory of Risk Homeostasis

Figure 4: The Theory of Risk Homeostasis
(Saxena, 2017)

In terms of scope, Sociological Theory addresses the broad societal and environmental factors that influence driving behavior across populations, making it valuable for understanding and shaping large-scale behavior patterns (Carter, 2017). In contrast, Domino Theory narrows its focus to specific accident sequences, which helps in pinpointing where and how to interrupt these chains to prevent accidents. Cause Theory, however, zeroes in on root causes of accidents, such as human error or mechanical failure, allowing a thorough examination of specific elements in individual incidents (Patriarca et al., 2022).

When applied to predictive modeling, Sociological Theory is effective in modeling societal factors that influence risky driving behaviors, aiding in initiatives like policy-making and urban planning. Domino Theory is valuable for forecasting and intervening in accidents with sequence-specific patterns, making it practical for direct, targeted safety measures. Meanwhile, Cause Theory is advantageous for predicting incidents by monitoring fundamental risk factors, such as fatigue or vehicle faults, to reduce similar accidents. Together, these theories enable a comprehensive approach to accident analysis and prevention, from societal trends down to individual accident components, supporting both broad-based and focused safety improvements (Nikita et al., 2018).

These theories enhance predictive modelling by creating a layered safety approach. The Sociological perspective enables policy and planning foresight, Domino Theory allows for targeted preventive actions within accident sequences, and Cause Theory offers deep-rooted incident prevention at the individual level (Ma et al., 2022). This holistic framework empowers decision-makers to proactively address risks across societal, sequence-specific, and foundational dimensions, making predictive modeling a powerful tool for both immediate and long-term accident prevention in road traffic management reducing the number of Road Traffic Deaths.

2.5 Machine Learning Models for Analysis of Road Traffic Accidents

Machine learning has found widespread application in traffic analysis, encompassing tasks from infrastructure design to predictive modelling, as demonstrated by various studies (Karimzadeh and Shoghli, 2020; Heyns et al., 2019; Gichaga, 2017; Pakgohar & Kazemi, 2015; Hadji Hosseinlou et al., 2018). Despite this, it appears to be a gap in research concerning a particular dataset. While artificial neural networks (ANN) and other machine learning models offer versatility and broad applicability, they come with trade-offs in terms of interpretability, transparency, and data requirements when compared to the Negative Binomial regression model. The selection between these approaches depends on the specific objectives of the analysis, the characteristics of the data, and the importance of interpretability and statistical inference in the research context (Linardatos, 2020).

We utilize text mining techniques on public accident information and documenetation, which contain eyewitness accounts of accidents, to extract significant categorizations using an machine learning model without supervision. The critical role that the classification of fatalities plays in the development of workable solutions emphasizes the significance of this investigation. Previous studies on this subject have predominantly employed the conventional statistical and regression methodology, which relies on the underlying assumption of linear and non-linear associations relating to output and input variables. Nevertheless, there has been a significant amount of research conducted on ML-based feature analysis in the past few years. The capacity of different Artificial Neural Networks (ANN) to predict, using different factors, the degree of injuries sustained in traffic accidents has been studied (Amiri et al., 2020, Shiran et al., 2021).

2.5.1 *Artificial neural network*

Amiri et al. (2020) employed Artificial Neural Networks (ANN) and an intelligent genetic algorithm that is hybrid to examine how psychological states and visual characteristics of older drivers (older than 65 years) impact prediction of the severity of RTAs. Artificial neural networks (ANN) exhibit greater accuracy in predicting less severe accidents compared to severe injury situations. The effectiveness of Artificial Neural Network (ANN) models decreases dramatically when used for multiclass classifications.

2.5.2 *Decision tree*

As a result, Decision Tree strategies for predicting accident severity have gained popularity in this area of study (Chen et al., 2020; Shiran et al., 2021; Zheng et al., 2016). According to the study done by (Chen et al. 2020), it is evident that Decision Trees (DT) are effective in identifying significant characteristics and their correlation with the severity of injuries. Furthermore, the precision of accident forecasting in decision tree (DT)-based methodologies is notably superior to that in artificial neural network (ANN)-based models, as stated by (Shiran et al. 2021).

2.5.3 *Support vector machine*

Sharma et al. (2016) used Support Vector Machines (SVM) with a Gaussian kernel to model the severity of traffic accident injuries as a classification problem. Because there are many contributing factors, several studies have looked at the application of SVM and Random Forest (RF) in forecasting the impact of severe road accidents (Mokhtari Mousavi et al., 2019, Sharma et al., 2016). The support vector machine (SVM) model demonstrated superior predictive accuracy compared to the multilayer perceptron network. To attain optimal performance with Support Vector Machines (SVM), it is necessary to ensure that each class in the dataset has an equal number of data points.

2.5.4 *Random forest*

A popular machine-learning technique for analyzing large datasets with multiple independent variables is random forest (RF), which is especially useful in the study of road accidents (Chen et al. (2020), Yan et al. (2022), and Mondal et al. (2020).). Mondal et al., 2020 examined crash data from four years (2015–2018) in Connecticut across five injury categories using this model. According to their findings, the main variables affecting the frequency of crashes

2.5.5 *Random forest bayesian optimization*

Yan et al. (2022) conducted research that combined RF with Bayesian optimization (RF-BO). They then utilized this RF-BO approach on the road accident dataset for the USA, specifically focusing on the period between March 2019 and February 2016. The model demonstrated superior predictive accuracy in comparison to conventional machine learning models. In addition to these, other boosting algorithms, including AdaBoost, XGBoost, and CatBoost, have been investigated as predictive models that enhance predictive accuracy while minimizing computing expenses For example, Parsa (et al. 2020) used XGBoost to find occurrences of traffic accidents. (Pradhan and colleagues, 2020; Parsa et al., 2020 Qu and associates, 2019 Ma and associates, 2021).

2.5.6 *Extreem gradient boost*

They evaluated their approach using a collection of real-time data that included information on traffic, weather and road infrastructure. The outcome demonstrated exceptional performance, with a detection accuracy of 99% while maintaining a false alarm rate of only 0.16%. The research carried out by Ma and colleagues in 2021 focused on using a CatBoost-based machine learning model to analyze the significant features and their impact on how well traffic accident predictions work.

2.5.7 *Generalised liner models for count data*

Non-negative integer count data are frequently heteroskedastic and right-skew, with variance generally rising as mean increases (Green, 2021). As can be observed in crash data where incidents without injuries are reported, these datasets typically contain a large number of zero values. The sample size constrains the actual data, even though count variables have an infinite range in theory. In these situations, conventional techniques for counting data analysis have been applied, such as hypothesis testing, analysis of variance (ANOVA), and ordinary least squares (OLS) regression (Paolella , 2018).

According to (Zheng et al., 2021) points out several methodological challenges in studies examining crash frequency. These challenges include dealing with temporal and spatial correlations, accounting for temporal-varying explanatory factors, and addressing omitted-variable bias. They noted that most crash frequency models typically use data aggregated over long periods, such as monthly or yearly intervals, rather than more precise time frames like hourly or daily data, which offer more detailed, time-sensitive insights. This reliance on broader time scales can introduce limitations, especially when important explanatory aspects—like the state of the weather and the quality of the roads, and traffic flow—can change rapidly over short intervals (Zheng et al., 2010).

When using data over shorter time frames, such as hours or days, two key challenges arise: (1) time-specific heterogeneity, where localized factors like micro-climates (e.g., snowstorms) or temporal patterns (e.g., weekends) can affect crash risks on the same road segment during the same period, and (2) the high frequency of zero observations, as shorter intervals often result in many instances with no crashes, leading to an overabundance of zero counts(Cheng , 2018). Additionally, with smaller time scales, It's possible to notice the same section of the road or time period repeatedly, introducing shared unobserved effects due to temporal and spatial correlations. To effectively address these challenges, appropriate statistical models are necessary to manage the excess zeros and account for the correlations present within the data (Ziakopoulos & Yannis., 2020)

2.6 Negative Binomial Model

To examine the connections between accidents, their characteristics, and accident sites, statistical models are frequently used. But previous research (Joshua & Garber, 1990; Miaou & Lum, 1993) has shown many drawbacks of linear regression models, leading to the adoption of better alternatives such as the negative binomial (NB) model, which employs data with Poisson means distributed gamma across crash locations and takes extra data dispersion into account (Afghari et al., 2019). The presence of "excess" zeroes, or zeroes when the actual number is more than what the Poisson or NB distributions suggest, is a common problem in accident data (Zamzuri, Sapuan, & Ibrahim, 2018). Here, "excess" does not refer to a total surplus but refers to a relative comparison, indicating that these models underpredict the number of zeroes in the data (Gogolev & Ozhegov, 2023).

Numerous research studies have examined road traffic death analysis in Kenya, with most academics focusing on the Negative Binomial Regression Model. When contrasting the Negative Binomial regression model with other machine learning (ML) models and artificial neural networks (ANN), interpretability and transparency are critical factors to take into account. While the Negative Binomial regression model offers a straightforward interpretation of coefficients and transparent functioning, ANN and other ML models are often opaque and challenging to understand. Additionally, the Negative Binomial regression model requires smaller datasets and less preprocessing compared to ANN and other ML models. While it performs well with linear relationships, ANN and other ML models excel in capturing complex nonlinear patterns (Belle & Paraptosis, 2021).

The most popular use of regression models has been to link accident frequency to explanatory variables. Traditionally, studies on typical accidents have mostly relied on ordinary Generalized linear regression models, which assume a normal distribution for the dependent variable, a constant variance for the residuals, and a linear relationship between the dependent and independent variables. An important factor in the model's outcome is the regression technique chosen (Chen et al., 2018).

Road traffic accident data is usually found to be over-dispersed, and using the Poisson regression to model over-dispersed crash data may result in inaccurate estimates of standard error. As a result, the Poisson-gamma model, also known as the negative binomial (NB) regression model, was developed to address this over-dispersion. (Ye et al., 2018). The NB models can handle over-dispersed data because they include an error term or component attached to the Poisson parameter that relaxes the assumption that the mean of crash count must equal the variance (Shaon et al., 2018).

According to (Macharia, 2019), to account for excess zeroes, zero-inflated probability models deal with two different states of the system: a zero-accident scenario (no accidents are ever recorded) and a non-zero accident scenario (accident frequencies are recorded according to certain known distributions, like the negative binomial distribution). This helps address the issues that arise with zero accident samples. Examples of these models include zero-inflated negative binomials and zero-truncated negative binomials (Workie & Azene, 2021).

2.7 Factors Influencing Road Traffic Accidents

95.0% of traffic crashes are thought to be caused by behavioural factors, and drivers' actions may be predicted using movement chance recognition and an understanding of activity risk projections. Although the role of human error in causing accidents has been long acknowledged, Recent significant efforts have been made to do comprehensive research on the consequences of human error in the series of circumstances resulting in mishaps.

Fatalities in road accidents are frequently linked to a few critical factors, such as secondary collisions, the failure to use seat belts, and riders neglecting to wear helmets (Bachani, 2017). He further highlights these as major contributors to the high number of casualties. As primary safety measures, seat belts and helmets play a vital role in protecting individuals during accidents; their absence significantly amplifies the risk of death in the event of a crash (Bhuiyan, et al., 2021).

2.7.1 *Age*

The factors that determine the unique characteristics of drivers were studied by (Rolison et al., 2018), such as age, gender, safety precautions taken, and propensity for risk) that impact the seriousness of accidents he focused on perspectives from law enforcement, driver opinions, and road accident records to evaluate and compare. The findings suggest adolescent drivers exhibit a greater propensity for risk-taking compared to older drivers. Furthermore, insufficient driving expertise and driver inattention are significant issues for inexperienced drivers. Middle-aged drivers with sufficient driving experience often face a high incidence of road accidents while intoxicated. Conversely, reasons for RTAs involving vehicles operated by elderly drivers are visual and cognitive impairments (Hammad et al., 2019; Rolison et al., 2018).

2.7.2. *Speed*

The level of volatility experienced during a collision greatly influences the severity of wounds incurred during the collision (Wali et al., 2020). Instability refers to the extent of fluctuation in driving patterns, encompassing factors such as speedy acceleration, abrupt stopping, erratic maneuvers, and hazardous interactions with other road users. These behaviors, especially when coupled with high speeds, drastically reduce a driver's ability to control the vehicle and respond to sudden changes in road conditions (McCarthy, 2024).

Driving instability at higher speeds increases the likelihood of severe accidents because it narrows the margin for error. Speed affects both the driver's reaction time and the distance required to stop safely. At higher speeds, even minor deviations in driving behavior, such as a quick lane change or sharp braking, can lead to significant loss of control. This instability is especially dangerous when interacting with other road users, as high-speed maneuvers often result in unpredictable and hazardous situations (Yang et al., 2019).

In their study, (Wali et al., 2020) used multinomial logit models to analyze the relationship between driving volatility and accident severity. The study identified a strong correlation between the severity of injuries and the level of volatility in the 30 seconds preceding a crash. This period, often marked by instability in driving behavior, becomes critical when speed is a factor, as the potential for a severe or fatal accident increases substantially.

Speed also amplifies the physical forces involved in a collision. As a vehicle's speed increases, the energy generated during a crash rises exponentially, which leads to more forceful impacts. Moreover, speeding reduces a driver's ability to perceive and react to hazards, such as pedestrians, cyclists, or unexpected obstacles. At high speeds, drivers are less likely to notice traffic signals, signs, or road markings in time to adjust their behavior appropriately. This increases the risk not only for the speeding driver but also for others on the road (Large ., 2019).

Additionally, external factors like road conditions, weather, and vehicle type can intensify the dangers of speeding. For instance, on wet or icy roads, driving at high speeds significantly reduces tire traction, leading to skidding or hydroplaning, which can result in severe accidents. Even vehicles equipped with advanced safety features may be unable to compensate for the reduced control at high speeds in such conditions (Han et al., 2021).

speed plays a decisive role in both the occurrence and severity of road traffic accidents. highlight the strong link between driving volatility and accident severity, particularly in the moments leading up to a crash. High speeds exacerbate the risks of instability, reduce control, and magnify the physical forces involved in collisions, making accidents more likely to result in serious injuries or fatalities. Reducing speed limits, enforcing traffic laws, and raising public awareness about the dangers of speeding are essential steps to improving road safety and reducing the impact of speed-related accidents (Winkler 2018).

2.7.3. *Risk appetite*

It was shown that a person's likelihood of contributing in a certain way was correlated with their assessed level of risk for that approach. contributing factors to certain auto accidents. The problem might be that we haven't been able to create enough high-quality theories to support our research methodologies, which could raise every relevant element needed to prevent. There exist some fundamental differences among accident causation theories. These differences may stem from variations in application, motivation, and focus. Additionally, there may be substantial differences in their inputs, outputs, and overall structure (Grant et al., 2018).

The rapid surge in motor vehicle ownership, combined with mixed traffic patterns and a lack of sufficient safety infrastructure, has substantially increased the risk of accidents. Many roads, initially designed for much smaller volumes of traffic, are now overburdened and unable to accommodate the growing number of vehicles effectively. This creates dangerous conditions, especially for vulnerable road users such as pedestrians and cyclists. According to studies by (Kim, Mannering, Shankar, and Ulfarsson 2010, as well as Reynolds, Harris, Teschke, Cripton, and (Winters, 2009), inadequate infrastructure remains a significant factor in the rising injury and crash rates for these groups.

Research highlights that infrastructure plays a pivotal role in mitigating risks. Multi-lane roads, for example, have been found to dramatically increase the danger to cyclists and pedestrians unless they incorporate dedicated tracks or lanes (Manivasakan et al., 2021). Roads with high traffic volumes present more hazards, particularly in urban areas, where pedestrian and cyclist interactions with motor vehicles are frequent. In contrast, smaller roads or streets with slower-moving traffic tend to be safer for non-motorized users. However, without sufficient infrastructure, such as pedestrian-only pathways, bicycle lanes, and safe crossing points, even minor roads can present significant risks (Aldred et al., 2018).

Several studies emphasize that the inclusion of these safety features is important in reducing accidents and fatalities. Dedicated lanes for cyclists and pedestrians not only provide physical separation from vehicles but also enhance overall traffic flow and safety. Similarly, proper crossing facilities, such as well-marked crosswalks and pedestrian bridges, lower the chances of accidents by providing safer opportunities for road users to navigate traffic. Ultimately, a lack of proper infrastructure puts both motorized and non-motorized road users at higher risk, underlining the need for targeted investments in road design and safety measures to adapt to the increasing pressures of modern traffic (Dubey et al .,2024).

2.7.4. *Environmental factors*

(Alogaili et al. 2020) presented the logit to examine the correlation between the driver's ethnicity, background, and level of education, and the impact of accident injuries. In addition to the unpredictable nature of driving conditions, several elements within a specific area, like residential or school zones, crossings caused by rain, number of lanes, and traffic signs. Additional research has investigated how natural environmental elements, According to (Pervez et al. 2022), (Bergel-Hayat et al. 2017), (Ahmad et al. 2020), and (Hammad et al. 2019), there is a growing probability of catastrophic road accidents due to factors like the kind of road and weather. In 2022, (Pervez et al., 202) discovered a positive correlation between hilly freeway tunnel groups and factors such as day, time, age, exhaustion, and speeding.

Although favourable weather conditions reduce the severity of accidents, unfavourable weather conditions increase the impact because drivers are more cautious. The study also demonstrates that lighting conditions have a role in determining the severity of road accidents. Specifically, accidents occurring at night in the absence of road lights can have dire consequences compared to other scenarios (Ullah et al., 2021).

Reducing road traffic accidents (RTAs) and deaths requires significant environmental adaptation. Reducing the frequency of accidents and associated injuries has been demonstrated to be possible by the implementation of environmental modifications such as such as area-wide traffic calming measures, speed cameras, 20 mph zones, speed bumps, dedicated cycling lanes, and school crossing patrols (Soathon, 2023). The main goals of environmental improvements are to lower traffic volume and speed, create safer areas for pedestrians and bicycles, and enhance overall road safety.

These changes are tailored to the unique environmental and social characteristics of different areas, whether urban, suburban, or rural. Urban environments often benefit from measures such as road narrowing, the creation of pedestrian zones, and traffic-calming strategies aimed particularly at protecting children (Anitpova et al., 2018). According to Wang et al., 2018) many studies supports that these measures reduce traffic speed and incidents of injury in densely populated areas. However, there is less research focusing on rural regions, which have distinct safety challenges due to less traffic infrastructure and higher vehicle speeds.

Rural initiatives, though less studied, are equally vital. Measures like building bypasses to divert traffic away from villages, improving walking and cycling routes, reviewing and reducing traffic speeds on narrow country lanes, and designating certain lanes as "quiet roads" (where vehicle access is restricted or speeds are heavily reduced) contribute to road safety in these regions. These interventions provide safer spaces for pedestrians, cyclists, and even horse riders (Kaiser et al., 2023).

Specific interventions, such as the use of red-light cameras, have been evaluated for their effectiveness. While they reduce right-angled collisions at intersections, they sometimes result in more rear-end collisions, raising questions about their overall safety benefits. Clearly marked cycling lanes, however, consistently show a reduction in injury rates when compared to unmarked roads. In addition, school crossing patrols have proven to significantly reduce the number of pedestrian accidents involving children near crossing sites (Sari, 2019).

A combination of safe routes to school programs, which integrate traffic-calming strategies, safer pedestrian pathways, and educational campaigns, can further enhance road safety for young people (World Health Organization, 2023). Educational and promotional interventions, particularly those that encourage the use of safety gear such as helmets or seatbelts, have been shown to lower injury rates. However, the evidence on the long-term impact of driver education programs or road safety campaigns remains limited, though they are believed to improve safety knowledge and behavior (Alonso, 2018).

(Tang et al., 2018) argues that, adapting the environment through targeted traffic-calming measures, infrastructure improvements, and safety education can significantly reduce road traffic accidents and injuries. These interventions need to be area-specific, with urban, suburban, and rural regions requiring different approaches based on their traffic patterns and road conditions. While many of these strategies are backed by research, ongoing evaluation and adaptation are essential to ensure their continued effectiveness in preventing accidents and saving lives (Pashayev, 2023).

2.7.5 *Lack of implementation of safety measures*

Nun et al., 2021 reported that 40% of drivers killed in road accidents in Britain and Wales in 2005 were not wearing seat belts, with most of these individuals aged between 17 and 29. Compliance with seat belt use tends to rise with age, as older drivers are more likely to wear them. Additionally, (Khan et al., 2020) found that seat belt avoidance is more common at night, leading to higher fatality rates in nighttime crashes. Anoxia, a condition where the airway is obstructed, cutting off the oxygen supply, is one of the leading causes of death in traffic accidents. Redmond (1994) highlighted that timely first aid can prevent many of these fatalities, particularly those caused by airway blockages. (Azami et al., 2021) noted that between 39% and 85% of pre-hospital deaths in road accidents could be prevented with proper intervention.

The "golden hour" refers to the critical time immediately after an accident when prompt medical attention is vital for saving lives. Administering first aid during this period significantly improves a victim's chances of survival before they reach the hospital (Sam et al., 2019). Thus, the use of seat belts and helmets, combined with quick access to first aid, plays an essential role in reducing fatalities and improving outcomes for crash victims.

2.7.6 *Fatigue*

According to research, sleepy driving-related incidents are among the riskiest due to their elevated probability of fatalities. The reason for this increased severity is that when a driver falls asleep at the wheel, they are unable to respond and prevent a collision by braking or steering (Darzi et al., 1998).) (Mahajan et al., 2021) found that sleep-related collisions are more likely to be deadly than other types of collisions because the driver loses control before the collision. (Young, 2020) found that sleep-related crashes are among the deadliest, with 50% more fatalities than other types of accidents. These studies were conducted in North Carolina. Moreover, (Mohammed et al.,) noted that these occurrences are associated with three times as many deaths

According to extensive research, drowsy or sleepy driving-related accidents are among the most dangerous and have a higher likelihood of resulting in fatalities compared to other types of road accidents (Adanu, 2021). One of the primary reasons for this heightened risk is that when a driver falls asleep at the wheel, they lose their ability to take corrective action, such as braking or steering, to avoid or mitigate a collision. This lack of response significantly increases the severity of the crash (Darzi et al., 1998). (Mahajan et al. 2021) further emphasized that sleep-related collisions are particularly lethal because the driver loses control of the vehicle entirely before impact, leaving no room for evasive maneuvers.

According to (Young, 2020) conducted research on the dangers of sleep-related crashes and found that these incidents are among the deadliest on the road. The study revealed that sleep-related accidents result in 50% more fatalities than other types of road crashes (Aljaban, 2021). Young's findings, based on data from North Carolina, underline the critical dangers posed by drowsy driving, (Alahmari et al., 2019) also found that sleep-related crashes are not only more fatal but are also associated with three times as many deaths compared to other types of road incidents.

The consensus from these studies highlights the extreme risk that sleep-related crashes pose to road safety. Unlike other accidents where drivers may have a chance to react, the complete loss of control in drowsy driving incidents makes them particularly devastating (Banz, 2019). Sleep deprivation impairs cognitive function, reaction time, and judgment, leading to a significantly higher risk of fatal outcomes.

In reviewing the literature, several themes emerge regarding the risks posed by drowsy driving. First, it is important to note that drowsy driving shares similarities with impaired driving due to alcohol or drugs in that both severely impair reaction time and decision-making abilities. However, unlike alcohol or drug-impaired driving, drowsy driving often goes unrecognized by drivers themselves, making it a more insidious danger (Lowrie, 2020). Many drivers are unaware of the extent to which fatigue affects their driving ability, leading to a false sense of security on the road.

Second, sleep-related crashes are often more likely to occur during late-night or early-morning hours when the body's circadian rhythms naturally induce sleepiness. Long-haul drivers, shift workers, and individuals who suffer from sleep disorders are at particularly high risk (Taylor, 2020). These findings suggest that public awareness campaigns targeting drowsy driving, similar to those for drunk driving, could be instrumental in reducing these preventable deaths. Moreover, technological advancements such as driver monitoring systems and fatigue detection technology in vehicles could play a pivotal role in alerting drivers when they are too tired to drive safely (Abbas et al., 2020).

2.7.7 *Vehicle age and condition*

One critical factor that significantly influences the severity of accidents is the age of the vehicle. According to Casado et al. (2020), individuals driving older cars face a substantially higher risk of fatality in the event of a crash compared to those driving more modern vehicles. The study found that drivers of vehicles registered between 2000 and 2003 had a notably lower average chance of dying in accidents compared to those driving cars registered between 1998 and 1999. This difference is primarily attributed to the enhanced safety features found in newer cars, such as improved crash-avoidance systems, better structural integrity, and advanced airbag technologies (Af Wahlberg et al., 2024).

The correlation between vehicle age and accident severity can be analyzed from several angles. Modern vehicles are designed with more sophisticated safety systems, including electronic stability control (ESC), anti-lock braking systems (ABS), lane departure warnings, and automatic emergency braking. These advancements are engineered to prevent accidents or at least reduce their severity by providing drivers with more control over their vehicles in critical situations. Additionally, newer cars tend to have crumple zones and side-impact protection that mitigate the forces of a crash, thereby increasing the likelihood of survival for occupants (Jayan et al., 2021).

However, the advantages of modern safety features may not always translate into reduced fatality rates in all driving conditions. while newer cars are generally safer, high-speed collisions on non-urban or rural routes continue to pose a substantial risk, even for those driving the latest models. Rural roads often have fewer safety measures like barriers, signage, or road lighting, and their higher speed limits amplify the force of impact during a crash. On these routes, even vehicles equipped with advanced safety technology may struggle to prevent fatalities, especially when factors such as driver fatigue, distraction, or poor road conditions come into play (World Health Organization, 2023).

This raises important questions about the interplay between vehicle safety features and the driving environment. Although newer cars offer a higher degree of protection in urban settings with lower speed limits and more controlled traffic environments, rural roads present unique dangers. These roads are often characterized by sharp bends, narrow lanes, and fewer traffic calming measures, which increase the risk of high-speed crashes. In such scenarios, even the most advanced safety systems may not be sufficient to protect occupants from severe injuries or death (schepers, 2019).

In addition, socioeconomic factors can also be linked to the age of vehicles and the likelihood of fatal accidents. Individuals with lower incomes may be more likely to own older vehicles due to affordability, and as a result, they are disproportionately exposed to greater risks in the event of a crash (Roll et al., 2022). The outdated safety features in older vehicles further compound this risk (Lord et al., 2019). This highlights a gap in road safety where those who can least afford newer, safer cars are often the most vulnerable to fatal outcomes.

Moreover, the psychological aspect of driving behavior on rural roads compared to urban environments should not be overlooked. Drivers may feel a false sense of security on familiar or less congested rural roads, leading to more aggressive driving or less attentiveness. This behavior, coupled with the fact that high-speed collisions on rural roads often leave little time for evasive maneuvers, exacerbates the dangers, even for those in modern vehicles (Hu et al, 2018).

2.7.8 *Disaster preparedness*

Access to emergency medical care, including hospitals and first aid supplies, remains a significant challenge in many developing nations, including Kenya. The availability of prompt and efficient emergency services is crucial in reducing the severity of injuries and fatalities resulting from road traffic accidents (Makagwa etal., 2024). However, reports reveal alarming gaps in the provision of such services. Only 16% of individuals injured in traffic accidents in Kenya received any form of first aid at the scene. This highlights pertinent issues as without immediate first aid, injuries that might otherwise be treatable can escalate in severity, increasing the risk of long-term disability or death (Ritha , 2023).

Moreover, 76.5% of injured people were transported to hospitals by well-wishers, typically other drivers or bystanders. While the altruism of these well-wishers is commendable, it also highlights the absence of a reliable emergency response system. Relying on untrained civilians to transport accident victims can further endanger lives, as the lack of medical knowledge or proper equipment to stabilize injuries during transit may worsen the victim's condition. This issue is particularly concerning in rural areas, where hospitals are often located far from accident sites, and delays in reaching medical facilities can be life-threatening (Ritha , 2023).

A mere 1.4% of traffic accident victims in Kenya were transported by the police, reflecting either a lack of police resources or an inefficient emergency response infrastructure. The role of law enforcement in such situations is critical, as they are often the first responders and can play an important part in administering or coordinating emergency medical care. The low percentage of police involvement suggests an urgent need for better training and resources for law enforcement personnel to respond to accidents effectively (Oloo, 2019).

Even more concerning is the fact that only 6.1% of accident victims were transported by ambulances. This figure indicates a severe deficiency in emergency medical services (EMS) across the country. Ambulances, equipped with paramedics and medical equipment, are essential for providing on-the-spot care and stabilizing patients before they reach the hospital (Hardofa et al., 2018). The absence of a well-functioning ambulance system means that many accident victims in Kenya are not receiving the timely, specialized care that could make the difference between life and death (Manoti , 2021).

In addition to the transportation issues, the availability of first aid supplies and trained personnel at accident sites is often insufficient. The lack of basic medical resources at the scene of an accident further contributes to the high fatality and injury rates in Kenya. A stronger focus on training first responders, including bystanders, in basic first aid techniques, and ensuring that emergency vehicles are better equipped and distributed across both urban and rural areas, could drastically improve survival rates following traffic accidents (Gatheca et al., 2017).

According to (Cholo et al,2023) the current state of emergency response to road traffic accidents in Kenya reveals significant inadequacies in the availability of first aid, professional medical transportation, and emergency services. These deficiencies, coupled with a lack of accessible hospitals, are critical barriers to improving survival rates for accident victims. Enhancing the capacity of emergency response systems especially by increasing the availability of ambulances, improving first aid training for civilians and law enforcement, and ensuring better access to medical supplies could have a profound impact on reducing traffic-related fatalities and injuries in Kenya(Kimani et al., 2020).

2.8 Conceptual Framework

The conceptual framework is grounded on both previous research and an analysis of current conditions related to road traffic safety. The dependent variables include various factors that contribute to road traffic incidents: driver behavior, pedestrian activity, pedal cyclist presence, obstruction, vehicle defects, and road defects. These variables influence the independent variable, which is the number of road traffic deaths as illustrated in figure 5 below.

FIGURE 5

Conceptual Framework

Independent Variables **Dependent variable**

(Y) –

Dependent Variable

1. Drivers Behaviour

2. Pedestrians

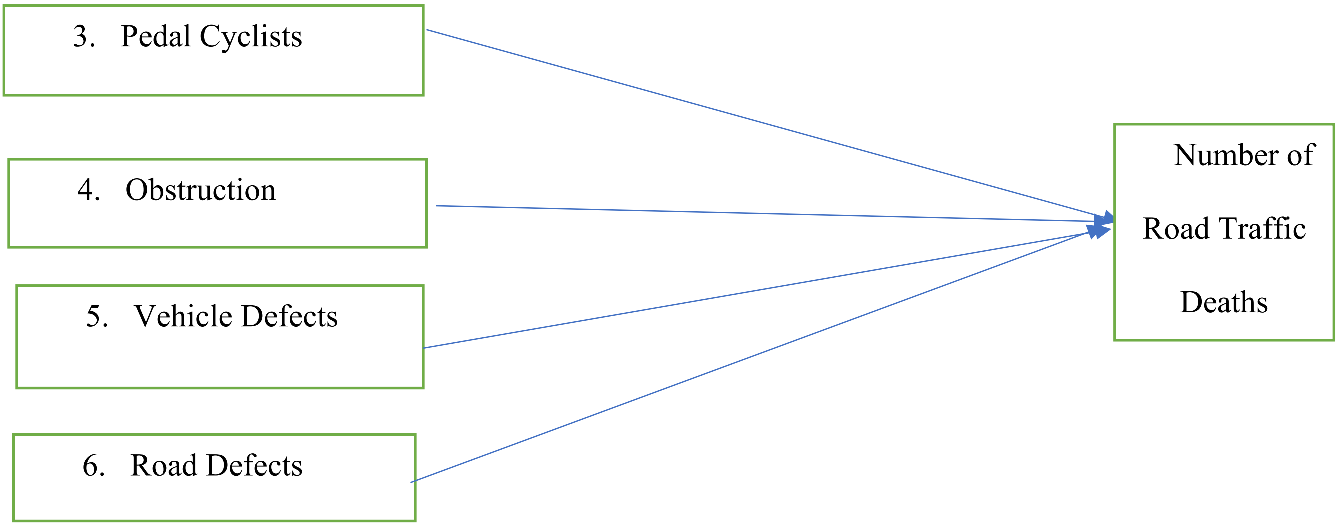

Figure 5: Conceptual Framework

TABLE 2

Operationalization of Model study Variable

2.9 Operationalization of Variable

Variable Type	Variable	Operational Definition	Measurement/Indicator	Data Source
Independent	Number of Road Traffic Deaths	The total count of deaths due to road traffic accidents within a specific time frame	Number of fatalities per year	Government traffic reports, police records
Dependent	Driver Behavior	Actions or reactions of drivers that may increase the likelihood of road accidents	Number of incidents involving speeding, drunk driving, or reckless driving	NTSA Road Accidents
Dependent	Pedestrians	The involvement of pedestrians in road traffic environments, including jaywalking or crossing without proper signals	Number of pedestrian-related accidents	Police reports, NTSA reports
Dependent	Pedal	The presence and	Number of accidents	Police reports,

Variable Type	Variable	Operational Definition	Measurement/Indicator	Data Source
	Cyclists	behavior of cyclists on roads, including compliance with traffic regulations	involving cyclists	NTSA reports
Dependent	Obstruction	Physical objects or barriers on the road that may impede normal traffic flow or cause accidents	Incidents caused by obstacles such as fallen objects, debris, or parked cars	Traffic authority data, incident reports
Dependent	Vehicle Defects	Mechanical or technical failures in vehicles that contribute to accidents	Number of accidents caused by brake failure, tire blowouts, etc.	NTSA accident Traffic Police Accident investigations Report
Dependent	Road Defects	Conditions of the road surface that may lead to accidents, such as potholes, uneven surfaces, or lack of signage	Number of accidents caused by poor road conditions	NTSA accident Traffic Police Accident investigations Report

Table 2: Operationalization of Model study Variable

2.9 For the operationalization of the model

To get the vector of fitted rates (λ), I fitted the Poisson regression model to the data set. Then proceeded to look for the value of α (this expresses variance as the mean) this examined wether the he aux OLS regression model was aligned to the data set. I will then use the α obtained to fit the Negative Binomial Regression model to the data set. I will then use the fitted NB model to predict expected counts on the test dataset, and lastly, assessed the goodness-of-fit of the NB model. (Cameron & Trivedi, 2013).

CHAPTER 3: RESEARCH METHODOLOGY

3.0 Introduction

The primary objective of any model-building strategy is to identify the most precise and succinct model that explains how a particular result (dependent or response) is connected to a group of independent factors (covariates). In this section, I outlined the procedures used to accomplish the study's goals. I focused on essential aspects such as study designs, the method for analyzing data, and the thoughtful consideration of moral considerations.

3.1 Research Design

Nairobi has the highest rate of traffic Jams; It’s the capital center of all major roads in all major towns. The National Transport Safety Authority (NTSA) provided data on daily traffic accidents that were specifically relevant to the study's period of interest, which ran from

January 2017 to December 2023. The NTSA routinely compiles information on traffic accidents from a range of sources, including police stations, hospitals, forensic medicine, and road organizations. The study used retrogressive designs using secondary data from the NTSA.

3.2 Data Collection

The National Transport and Safety Authority (NTSA), the Kenya Bureau of Statistics, and the Nairobi Traffic Police post were among the several sources of data used in the research. Upon collection, the data underwent thorough checks for completeness. Subsequently, Python programming was utilized to clean, edit, and eliminate any missing values, facilitating comprehensive data analysis.

Specifically, the information was taken from the NTSA's web database, which is in charge of guarding Kenya's transportation and safety regulations. To increase transparency and public awareness of safety issues, the NTSA provides the following two main categories of data: reports every day and nationwide reports on fatal accidents. The assembly process submitting a formal request to the CEO NTSA upon approval I received the requested data Via email. These data are typically presented in Excel documents, examples of which are provided below.

The daily reports furnished detailed information on fatalities and injuries, with categorization into groups such as pedestrians, passengers, drivers, motorcycle passengers, pedal cyclists, and motorbike cyclists. These reports from the agency detail fatal incidents, specifying the location (County), date, victim information, and category. The fatal accident report, on the other hand, includes information on a number of different topics, such as the victim's name, age, gender, and cause code, along with information on the time, Base/Subbase, County, Road, Place, and involved motor vehicle (MV). Time, County, a few key details about the accident, and victim information will be our main areas of concentration. There are 47 regions (counties) in the dataset, which covers the entire nation. This comprehensive approach ensures a robust foundation for our study, allowing for a thorough examination of road traffic deaths in Nairobi.

3.3 Limitations of Secondary data collection

The use of secondary data from NTSA on Road Traffic Deaths had several limitations, primarily due to inconsistencies in data collection standards from, underreporting, and missing information. Data collection practices vary widely between regions, affecting the consistency of data on critical variables, such as definitions of death (e.g., whether death is counted only if it occurs within a certain timeframe post-accident) or specific demographic details. Furthermore, underreporting is common, particularly in areas with limited resources or less stringent reporting requirements, which may omit certain fatalities (e.g., deaths occurring off-site or delayed by several days) from official statistics. Missing data is also frequent in secondary datasets, with gaps particularly evident in fields like accident location, time, or victim characteristics, limiting comprehensive analysis and insights (Wen et al., 2021).

To address these issues, data cleaning and imputation were applied to improve the dataset's completeness and reliability. Mean imputation, a common method, involves replacing missing values with the mean of observed values for that variable. This technique is simple and preserves the sample size, but it can introduce bias by reducing variability, especially if the data is not symmetrically distributed (Lin et al., 2020). For the missing cases of the study, I substituted them with the mean value of Road Traffic scores to maintain a complete dataset.

By applying these techniques, researchers can improve the completeness and consistency of secondary data on road traffic deaths, enabling more robust analyses and valuable insights for policy and prevention efforts. However, even with imputation, secondary data may lack the granularity and real-time accuracy of primary data sources, which can still influence the precision of predictive findings.

3.4 Data analysis

In this scenario, the objective of regression analysis is to model the dependent variable (deaths) as the outcome estimate using some or all of the explanatory variables. For the study variables we have

$$\mu_i = exp(ln(t_i) + \beta 1 Drivers\ Behaviour\ + \beta_2 Pedestrians\ + \cdots + \beta_k Road\ Defects\ )$$

$$\mu_i = exp\left(ln(t_i) + \beta 1 x_i + \beta_2 x_{2i} + \cdots + \beta_k x_{k_i}\right)$$

$$P_r(y = y_i \setminus u_i \alpha) = \frac{\Gamma(y_i + \alpha^{-1})}{\Gamma(\alpha^{-1})\Gamma(y_i + 1)} \left(\frac{1}{1 + \alpha u_i}\right)^{\alpha^{-1}} \left(\frac{\alpha u_i}{1 + \alpha u_i}\right)^{y_i}$$

Where β 1 is the intercept Using a set of data, the regression coefficients β1, β2, …, βk represent unknown parameters that are estimated (Hilbe, 2011). The symbols for their estimates are b1, b2…, bk. Where (X1…Xk) are the independent variables below

3.5Study Variable

The rate of Road Traffic Death is the study's outcome variable, this is a count as the number of deaths is only expressed as whole numbers. The phrase "cause of the accident" refers to the error that caused a particular accident. It is assumed that the observed outcomes on the same objects will be related. Pearson correlations for the aggregate data were done to determine the strength between the dependent variables

$$u = e^{\Lambda}(\beta_o + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)$$

Where B1, B2…BK is the correlation coefficient X1, X2… Xk Factors influencing accidents

E (Yi) = Expected number of deaths

3.6 Target Population and Sample Size

The prevalence formula to look for the sample size in the study

$$n = \frac{z^2 P(1-p)}{d^2}$$

All (RTDs) that occurred in Nairobi in the years January 2017 and December 2023 will be taken into consideration.

n = sample size,

z = critical value (1.96),

d = margin of error (0.05),

P = proportion (0.5).

3.7 Negative Binomial Distribution

A fixed number of trials with a probability of success (P) and a probability of failure (q) make up the binomial distribution. By incorporating a gamma-distributed error component, the negative binomial approach modifies the assumption of equality between the mean and variance.

$$e^{\varepsilon_i} = gamma\ distributed\ error\ term\ with\ mean = 1\ and\ Variance = \sigma^2$$

The error changes the variance and the mean.

$$Var(y_i) = E(y_i)[1 + \sigma E(yi)]$$

$$Var(y_i) = E(yi) + \sigma E(y_i)^2$$

3.8 Model Cross Validation

Cross-validation is a valuable technique in negative binomial regression for assessing robustness and predictive accuracy, especially with over dispersed count data, such as road traffic deaths. Traditional evaluation metrics, including mean absolute error (MAE), root mean square error (RMSE), and mean squared error (MSE), are commonly used to assess model fit. Additionally, deviance, which measures the discrepancy between observed and predicted values, is frequently employed to evaluate goodness of fit for count data models (Oluwajana et al., 2022).

Since negative binomial regression is suited to over dispersed data, cross-validation also enables checking the dispersion parameter across folds to ensure consistency, indicating that the model effectively accounts for data variability (Sidumo, 2024).

3.9 Model Validation

To evaluate the model's performance in mapping the relationship between X (feature) and Y (target), loss functions compare the predicted values with the actual values. Model refinement is guided by the loss, that is, the variation between what happened and what was anticipated. Values. Higher losses indicate worse performance, necessitating modifications for the best possible training. The evaluation will include a root mean square error.

3.9.1 *Root mean squared error (RMSE)*

It is a metric used in statistics and machine learning Root Mean Squared Error, or RMSE, is a measure of a predictive model's accuracy. Through the process of squaring the errors, computing the mean, and calculating the square root, it quantifies the variations between the expected and actual values (Chico et al., 2021). The model's performance is provided by the RMSE, where lower values correspond to higher predicted accuracy. It is simple to comprehend RMSE. Many optimization methods like it because it is easily differentiable and has a simple computational structure. Because of the square root, RMSE penalizes errors less than the Mean Square Error does.

3.9.2 *Akaike information criteria*

Numerous linear regression models utilize the coefficient of determination (R2) test to assess the degree to which the model fits the data. According to (Zhang et al., 2023), I will use the Bayesian information criterion (BIC) and the Akaike information criterion (AIC) in my research. (Hilbe, 2014) claims that AIC is one of the most commonly used methods to analyze the model fit, the model deals with the probability of overfitting and underfitting, hence the value with the least AIC is the model with the least fit. The formula for the model evaluation is

$$\text{AIC}=2\text{K}-2\log(\hat{L})$$

3.9.3 *Bayesian criterion model*

When choosing a model from a limited number of options, The Schwarz information criterion or the Bayesian information criterion (BIC) can be applied. (also known as SIC, SBC, or SBIC). Models with lower BIC are typically taken into consideration (Shen et al., 2021). It is intimately associated and somewhat based on the likelihood function and the Akaike information criterion (AIC). More parameters can be added to a model to raise its maximum likelihood, although doing so may cause overfitting. The number of parameters in the model are penalized in both BIC and AIC to address this issue; for sample sizes higher than seven, the penalty term in BIC is greater than in AIC (Ding et al., 2017).

$$\text{BIC} = ln(n)K - 2\,ln(\hat{L})$$

3.9.4 *Residual analysis*

Complete residual analysis will be used, just like in any regression study. To check for outliers and curvature, the residuals will be plotted against a variety of additional factors, including the response variable and the regressor variables (Martin et al., 2017).

CHAPTER FOUR: RESEARCH FINDINGS AND DISCUSSIONS

4.0 Introductions

The section highlights the Road Traffic Accident data collected from 2017-2023 from NTSA, presenting key findings. The primary objective of the research was to employ the Negative Binomial model to examine traffic fatalities in Nairobi County. This chapter summarizes the research results derived from NTSA secondary data, including an inferential analysis of the 3,164 data points collected. The sample size is sufficient to make inferences about the broader population within Nairobi County. This analysis is also compared to previous studies, addressing inconsistencies observed in those studies.

4.1 Descriptive Statistics

secondary information obtained from the National Transportation and Safety Authority (NTSA) included 3,164 observations across 9 variables. This data was initially gathered through accident reports submitted to the NTSA by the Traffic Police Department. The study focused on accident data from 2017 to 2023, with the number of deaths serving as the dependent variable. Prior to analysis, data preparation was carried out, which involved the removal of missing values to ensure accuracy. From the analysis, it was observed that a total of 3,163 road accidents deaths within 2017 – 2023 the overall mean value across the dataset was 1.022447, with a standard deviation of 0.212962. This indicates relatively low variability in the data, suggesting that the values are closely clustered around the mean. Below, the mean values for different years are presented, highlighting any significant differences or trends ((Govender &Sivakumar, 2020).

In comparison to other studies its shows

TABLE 3

Table showing descriptive analysis of the Data

No	YEAR	DESCRIPTIVE ANALYSIS RESULST
mean	1.022447	2020.113464
count	3163.000000	3164.000000
std	0.212962	1.958490
min	1.000000	2017.000000
25%	1.000000	2018.000000
50%	1.000000	2020.000000
75%	1.000000	2022.000000
max	9.000000	2023.000000

Table 3: Table showing descriptive analysis of the Data

The descriptive statistics provide a clear and informative insights of the dataset, highlighting both the central tendencies and the spread of values within each variable. For the "No" variable, the statistics reflect a highly consistent dataset, with most values centered around 1, as seen in the mean (1.022), median (1), and low standard deviation (0.213). This high level of consistency suggests reliability in the dataset and minimizes noise, making it suitable for models and analyses that benefit from stable, repeated values. The few higher values, up to a maximum of 9, offer potential insights into exceptional cases that could be analyzed further to understand unique occurrences or factors within this context.

For the "YEAR" variable, the six-year range from 2017 to 2023 provides a reasonably broad view of data across time, allowing for trend analysis and insight into temporal patterns, particularly as the data is well-distributed across this period. The mean year of 2020 and moderate standard deviation indicate that the dataset covers recent data points, making it relevant for analyzing trends that can inform current or near-term scenarios. The large count (3164 entries) offers a robust sample size, which supports statistically meaningful conclusions and provides a strong basis for further analysis across subsets or specific years within the range.

The count of missing data was in total; the description data is illustrated as below.

FIGURE 6

Graph showing the years against the fatality rates

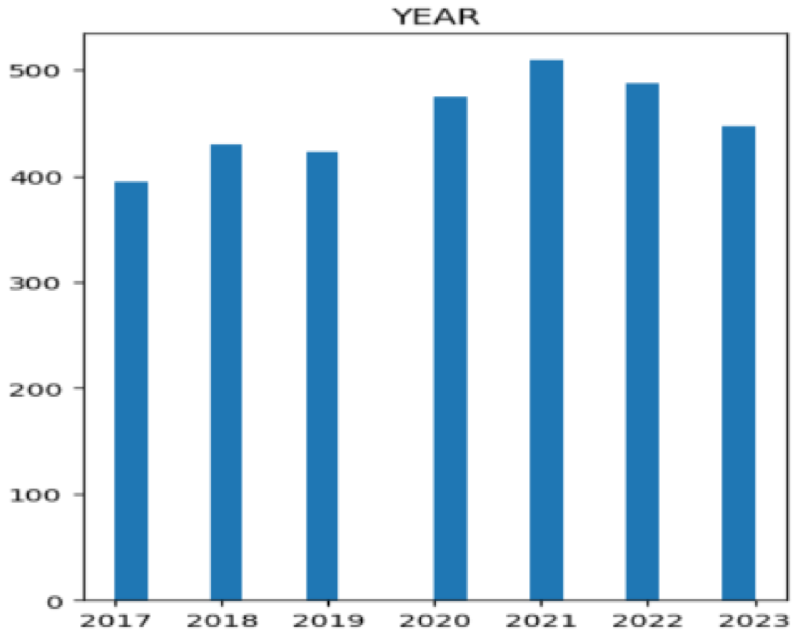

Figure 6: Graph showing the years against the fatality rates.

The graph depicting the number of fatalities over the years reveals a peak in 2021, with 500 recorded fatalities. However, this figure declined in subsequent years, dropping to 480 in 2022 and further to 470 in 2023. This decrease could be attributed to NTSA's efforts and various awareness campaigns, as supported by Muguro's 2020 study. Additionally, the daily reports of fatal incidents have steadily decreased. In 2016, over 200 entries were recorded, while by 2019, this number had fallen to fewer than 20. This significant reduction in data entries necessitated the use of interpolation to estimate monthly figures (Muguro, 2020).

FIGURE 7

Average Rate of Fatalities per Day against Days of the week

4.2 Average Review of Fatalities Per day

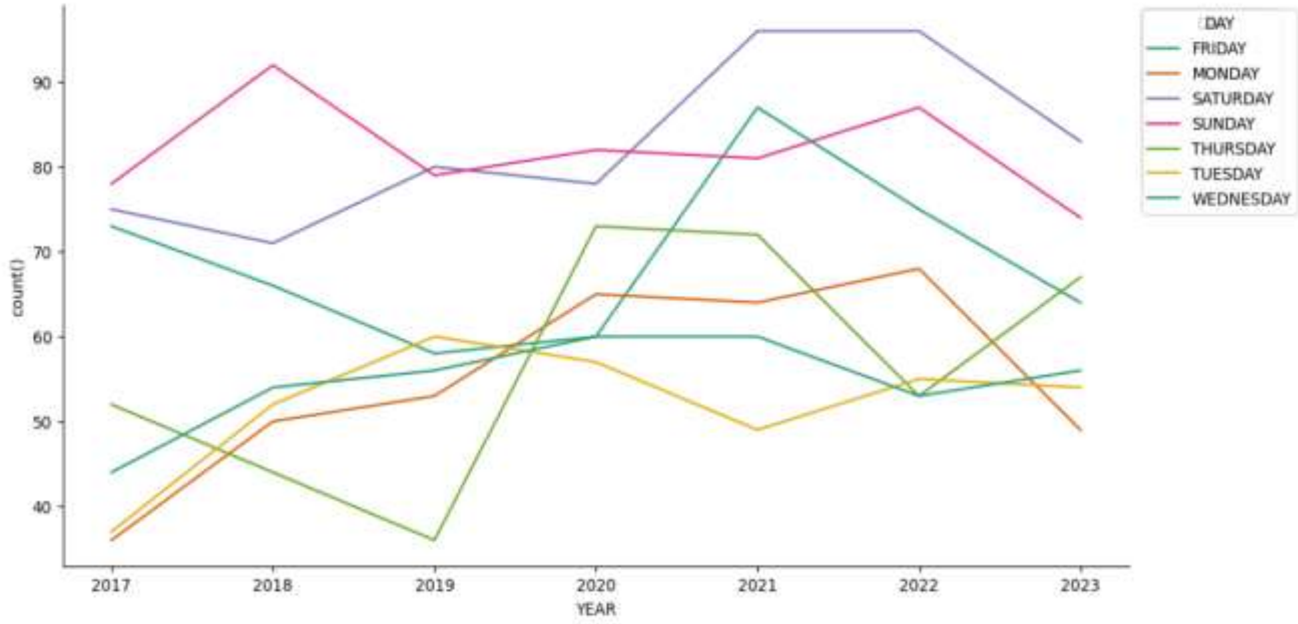

Figure 7: Graph showing Average Rate of Fatalities per Day against Days of the week

The analysis of fatal road deaths by day of the week over several years reveals significant trends. In 2017, Sundays saw the highest number of fatal accidents, a pattern that continued into 2018, with Sundays recording 90 fatal accidents. In 2019, fatalities on Sundays dropped to 78, and in 2020, there were 80 fatalities on the same day. However, from 2021 to 2023, Saturdays emerged as the most dangerous day for fatal accidents. In 2023, fatalities were distributed across the week as follows: 566 on Mondays, 469 on Tuesdays, 521 on Wednesdays, 531 on Thursdays, and 645 on Fridays. In comparison, 2022 saw even higher numbers: 656 fatalities on Mondays, 551 on Tuesdays, 557 on Wednesdays, 527 on Thursdays, and 669 on Fridays.

FIGURE 8

Number *of RTD* against the year

4.3 Average Number of Fatalities Per Year

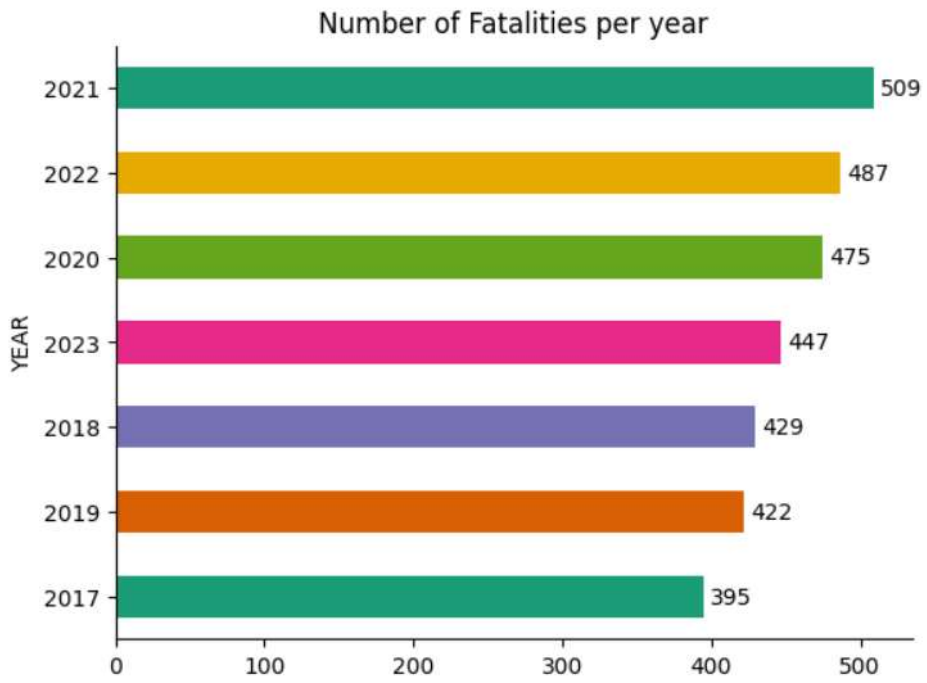

Figure 8:Graph showing the Number of RTD against the year

The analysis of road traffic fatalities in Kenya from 2017 to 2023 reveals a fluctuating but generally declining trend, with fatalities peaking at 509 in 2021 before falling to 447 in 2023. While these declines suggest some improvement in road safety efforts, the overall number of fatalities remains concerning. Eighty percent of road traffic deaths occur in middle- and low-income countries worldwide, which have been disproportionately affected by traffic accidents (Abegaz & Gebremedhin, 2019). Pedestrians, cyclists, and motorcyclists are among the vulnerable road users most at risk, especially in African and Asian countries, where fatality rates per vehicle remain significantly higher than in developed regions (Al-Madani et al., 2019). The data suggests some improvement in road safety efforts, although fatalities remain concerning.

4.4 Analysis of Number of Accidents Per Hour.

FIGURE 9

Number of RTA Against the Hour of The Day

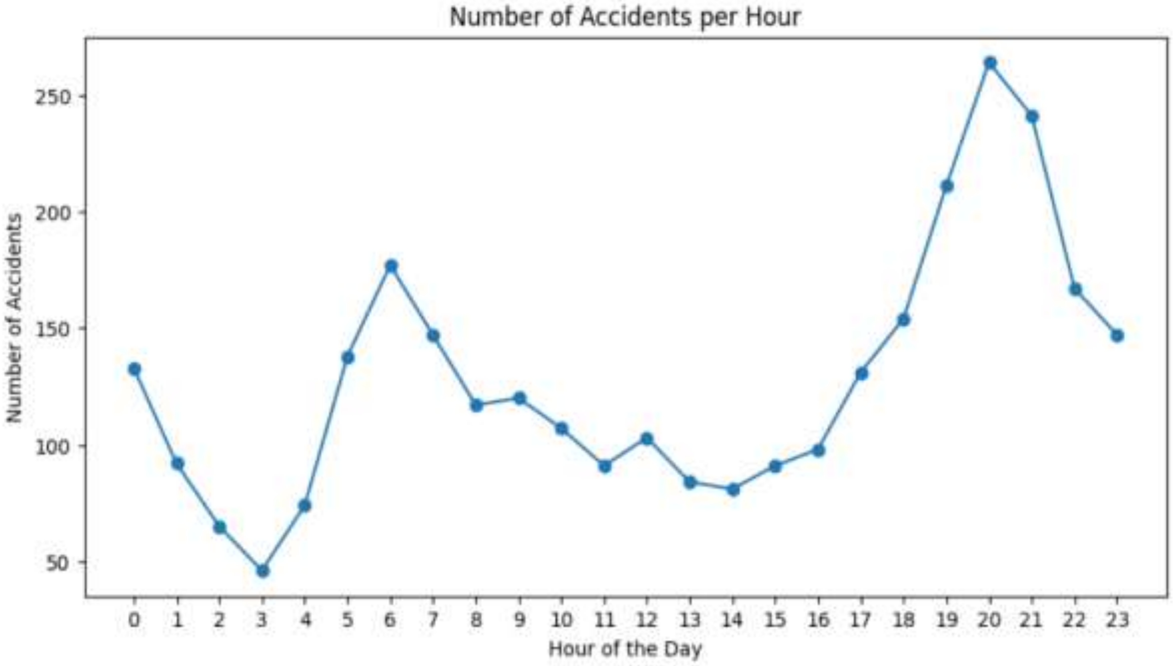

Figure 9: Graph showing the number of RTA against the hour of the Day

The analysis indicates that road accidents peak at 8:00 p.m. and the highest death rate is at 6:00 a.m. These times are significant because they align with key daily routines. At 6:00 a.m., many people are beginning their morning commute to work, which coincides with an excessive number of cars on the road. The combination of early morning darkness, potentially lower visibility, and the rush to reach workplaces contributes to the increased risk of severe accidents, reflected in the higher death rate during this hour.

Similarly, the 9:00 p.m. peak in accidents can be linked to the time when people are returning home after work or evening activities. Fatigue, decreased visibility at night, and higher traffic volumes can all contribute to the spike in accidents during this time. The data shows the critical role that traffic volume and time of day play in road safety, especially during the hours when people are either starting or ending their workday. As evidenced in the graph below

In comparison to other research, (Kim et al.,2022, Salon et al., 2028), as well as highlights that the safety of pedestrians and cyclists is largely compromised by insufficient infrastructure. Their studies indicate that infrastructure is an important component in assessing the risk. of injuries and crashes. For instance, they found that multi-lane roads pose a significantly higher danger to pedestrians and cyclists unless separate paths are integrated into the road design (Soathong, 2019). Larger roads present greater risks compared to smaller roads, whereas the presence of dedicated pedestrian and bicycle lanes and adequate crossing facilities is associated with reduced accident risk.

FIGURE 10

Number Of Fatalities *Against the Cause* Time Frame

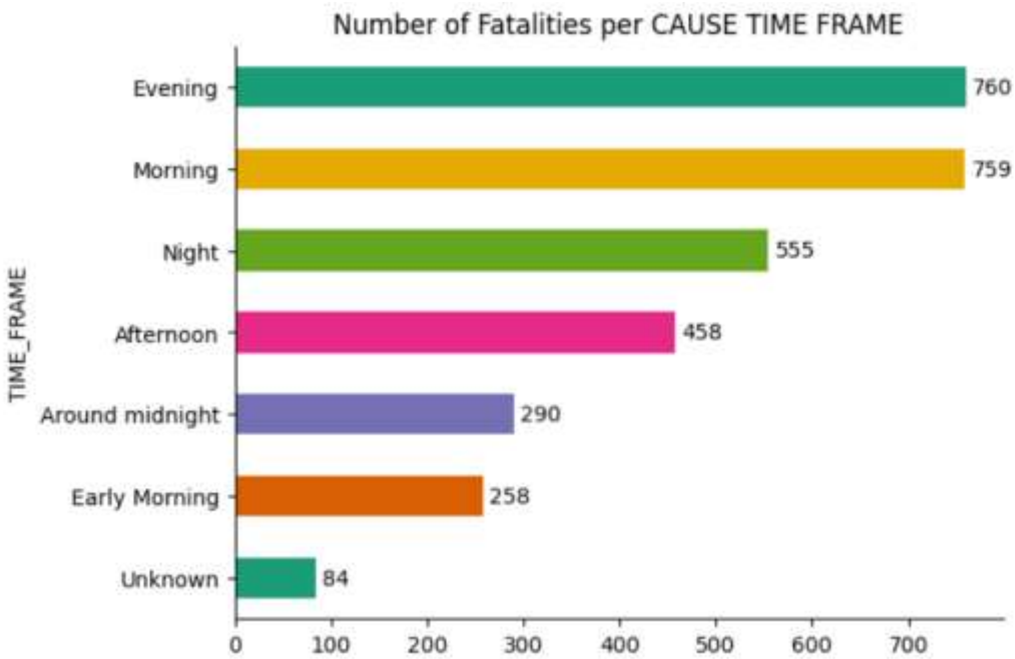

Figure 10: Graph showing the Number of Fatalities against the Cause Time Frame

From the graph most accidents happen during the evening the same can be attributed to the mist and darkness and fatigue after work and rush to get home after office hours, the value is closely followed by the morning range were the same could be attributed to the rush to get to the office and rush during the morning hours.

The results from the study echo many of the key findings and themes identified in the broader When evaluating the risk, literature is a crucial tool. similar to Kenyan. Globally, the complexity of improving road safety is underscored by persistent challenges such as inadequate infrastructure, poor enforcement of traffic laws, and limited urban planning, particularly in rapidly growing cities (Hassan et al., 2022). These issues are prominent in Kenya, where despite a reduction in road traffic fatalities, the country continues to face considerable barriers due to underdeveloped road infrastructure, outdated vehicles, and inconsistent law enforcement.

The findings align with global patterns seen in other African nations, where economic growth and urbanization have increased motorization, placing strain on existing road safety measures. Kenyan urban centers, such as Nairobi, experience heightened risks for vulnerable road users—pedestrians and cyclists—whose safety is often compromised by the lack of adequate infrastructure. Similar to what Kim et al. (2010) and Reynolds et al. (2009) highlighted, the absence of dedicated pedestrian and cycling lanes on major roads contributes significantly to the high rates of fatalities and injuries.

4.5 Number of Fatalities Per Type of Case

FIGURE 11

Fatalities *Against* the Type of Cause

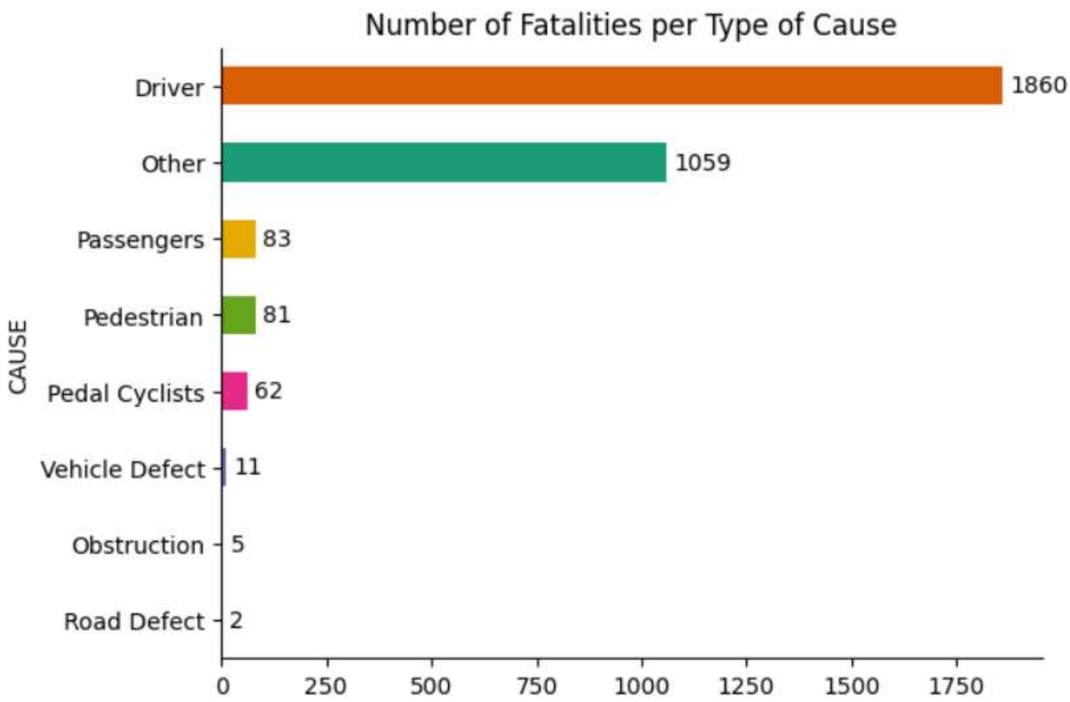

Figure 11: Number of Fatalities against the type cause

The majority of road traffic fatalities recorded by NTSA involve motor vehicle drivers, with a total of 1,860 deaths, though some causes of fatalities remain unverified due to incomplete data. Passenger fatalities accounted for 83 deaths, pedestrian deaths totalled 81, cyclists numbered

The findings from the current study on road traffic fatalities in Kenya show that motor vehicle drivers account for the majority of deaths, which closely aligns with earlier studies such as (Foley et al., 2019) in Leeds, United Kingdom. Both studies highlight driver behaviors, such such as overspeeding, improper overtaking, inattention, and failure to yield, as major causes of traffic accidents (Grasso et al., 2022). These shared issues point to a commonality in driver-related crashes across different regions. In both Kenya and Leeds, speeding, poor judgment, and loss of control are key factors leading to accidents (Dotse , 2019).

The Kenyan study, however, also identifies systemic issues that exacerbate these behavioral problems, such as the poor state of infrastructure, lax law enforcement, and inadequate road conditions (Muguro et al., 2022). These factors, while present in developed nations like the UK, appear to have a more severe impact in Kenya due to the lack of effective interventions. In contrast, regional differences become evident when comparing Kenya to other parts of the world, such as Asia (Huh et al., 2018). In countries like Hong Kong and Korea, a larger proportion of road fatalities involve pedestrians, with vulnerable road users (VRUs) comprising up to 89% of deaths in some areas.

This is significantly higher than the pedestrian fatalities in Kenya, though the trend is similar, with pedestrians being the second-largest group affected after drivers (Yasin, 2023). The higher share of motorcyclist fatalities in countries like Malaysia and Taiwan (over 50%) highlights the importance of contextual factors, such as the prevalence of motorcycles in these regions, compared to Kenya, where vehicle drivers dominate the fatality statistics.

Ultimately, while behavioral and systemic factors lead to road fatalities globally, the emphasis varies by region (James, 2020). In Kenya, the issue is compounded by infrastructure deficits and weak enforcement, while in countries like Hong Kong and Singapore, vulnerable road users face the most significant risk, indicating that targeted interventions should be tailored to address the specific risks in each region (Li, 2023).

4.6 Number of Fatalities per weekday

FIGURE 12

Fatalities Against the Week

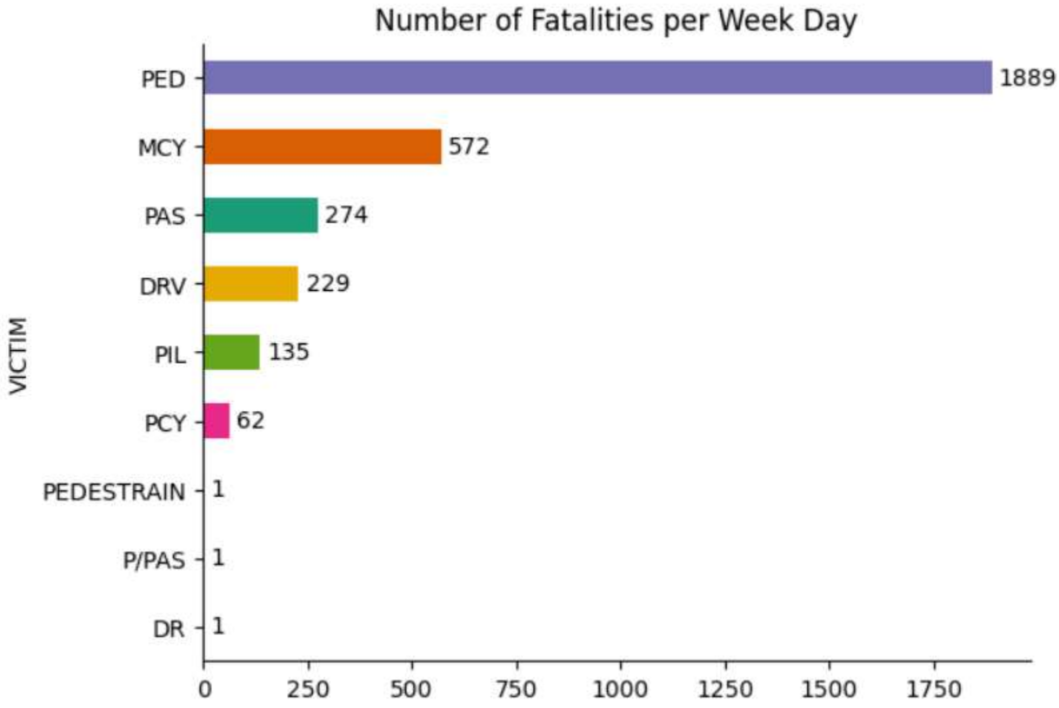

Figure 12: Number of Fatalities against the week

The analysis indicates that the greatest quantity of incidents occurring during the week involved pedestrians, with a total of 1,889 incidents. Motorcycle passengers accounted for 572 fatalities, while passenger fatalities reached 274. Additionally, accidents caused by drivers resulted in 229 fatalities, followed by 135 pillion passengers and 62 other passengers who lost their lives.

The results from the analysis demonstrate that in Kenya, pedestrians, motorcycle passengers, and general passengers represent the majority of casualties in road traffic accidents (Ngari, 2021). Pedestrians accounted for the highest number of accidents, followed by motorcycle passengers and drivers. This is consistent with trends observed in African and Middle Eastern countries, where pedestrians are among the most vulnerable road users, often representing a significant proportion of fatalities (Khan et al., 2020). In some Middle Eastern countries, pedestrian deaths can account for over 30% of all road fatalities (Gorell, 1997). In Kenya, the vulnerability of pedestrians stems from factors such as ignorance of traffic signs, influence of alcohol or other substances, poor judgment, and a lack of anticipation, which aligns with findings from other regions (Neil, 2023).

Kenya's road traffic accident trends align with broader regional patterns in Africa and Asia, particularly regarding the vulnerability of pedestrians, the significant role of passengers in accidents, and the high involvement of younger, economically active individuals in fatalities (Cassarino et al., 2018). Despite these similarities, the specific behaviors leading to accidents, such as passenger-induced distractions and misjudgments by pedestrians, reflect unique local challenges that require targeted interventions (Mohammed, 2019).

4.7 Most Accident Places

From the word cloud and analysis, most fatal road accidents occurred along key roads such as Mombasa Road, Waiyaki Way, and Thika Road, particularly near roundabouts and junctions.

FIGURE 13

Areas Most Prone To Accidents

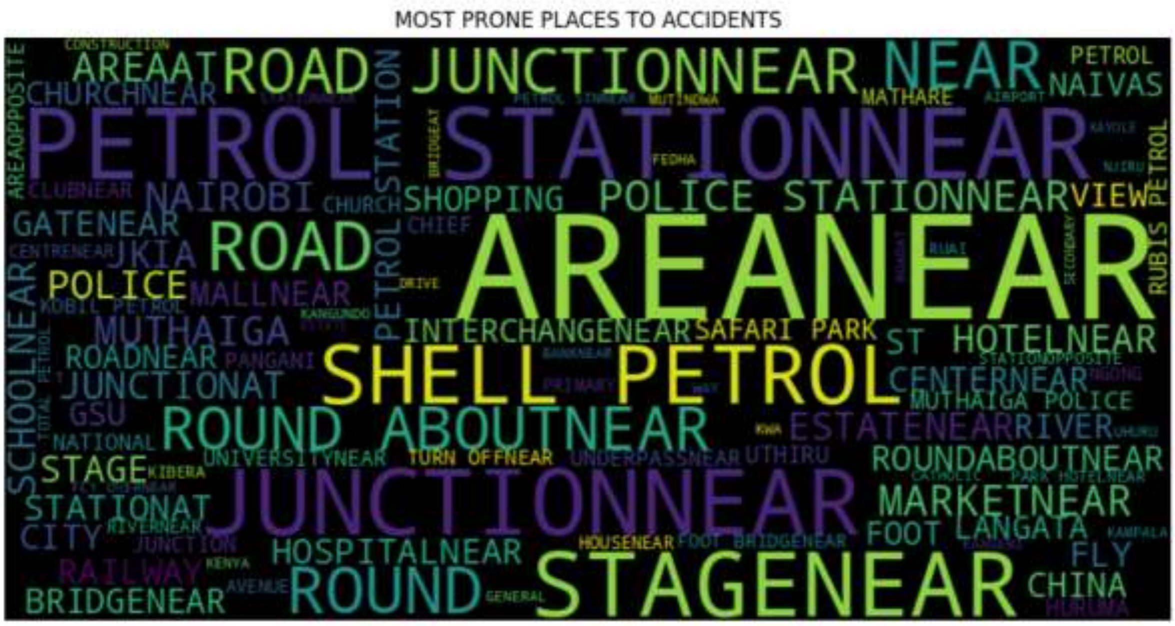

Figure 13: Word Cloud showing areas most prone to accidents

4.8 Inferential Analysis

To address the objective of predicting road traffic deaths in Nairobi, the Negative Binomial Regression model was selected for its suitability in handling count data with overdispersion, where the variance exceeds the mean. The dataset spans from 2017 to 2023, with a total count of 3,159 observations. The mean year in the dataset is approximately 2020, with a standard deviation of 1.96, indicating a relatively even spread across this timeframe. This temporal range enables the model to capture both current and evolving trends in road traffic deaths. For the model, the count of road traffic deaths serves as the dependent variable, while independent variables might include time (year), as well as other relevant factors (e.g., traffic density, road conditions, or seasonal patterns) if available. These variables together would help the model account for year-to-year fluctuations in road traffic deaths and reveal how specific factors influence these variations.

The Negative Binomial Regression model estimates coefficients for each independent variable, allowing for the interpretation of their impact on the likelihood of road traffic deaths. For instance, a positive coefficient for the "year" variable would suggest an upward trend in road traffic deaths over time, possibly reflecting increased urbanization or vehicle density. Given the model's structure, it is particularly adept at handling the overdispersion commonly observed in count data, such as accident statistics, which often have variance exceeding the mean. The descriptive statistics, such as the minimum (2017) and maximum (2023) values for the year variable, highlight the period over which the data is consistent, ensuring that the model remains relevant and accurate for understanding near-term trends in road traffic deaths.

TABLE 4

Inferential Analysis

Year	Count Data
count	3159.000000
mean	2020.112377
std	1.958330
min	2017.000000
25%	2018.000000
50%	2020.000000
75%	2022.000000
max	2023.000000

Table 4: Inferential analysis of the raw data

4.9 Negative Binomial Model Results

From the analysis and building the Negative binomial model , the analysis of the model for development for the Road Traffic Accidents.

$$\mu_i = exp(ln(t_i) + 0.3646 Drivers\ Behaviour\ + 0.4439 Pedestrians + 0.5871 Road\ Defects + 0.4941 Road\ Defects\ )$$

$$\mu_i = exp\left(ln(t_i) + 0.3646x_i + 0.4439x_{2i} + \quad 0.5871x_{3i}\ + 0.4941x_{k_i}\right)$$

AIC = 4689

From the analysis below we have the following

i. t_i: is likely the exposure or time variable related to road traffic incidents. It could refer to the time or the total amount of traffic over a given period. The logarithm t_i of is used to model the base rate of accidents before factoring in other variables.

ii. exp: The function ensures that the output μi which could be interpreted as the predicted number of road accidents fatalities, remains positive. This is common in models dealing with count data

4.9.1 Variables

i. **0.3646 (Drivers' Behavior):** This coefficient quantifies the effect of drivers' behavior on accident rates. A positive value means that poor driver behavior increases the number of accidents.

ii. **0.4439 (Pedestrians):** This reflects the contribution of pedestrian actions or conditions. Again, a positive coefficient implies that pedestrian-related factors contribute to an increased accident rate.

iii. **0.5871 (Road Defects):** This is the most significant coefficient, indicating that road defects (like potholes or poor road conditions) have a substantial effect on accident rates.

iv. **0.4941 (Other Road Defects):** This likely represents additional factors related to road conditions, possibly overlapping but distinct from general road defects.

4.10.1 *Generalized Linear Model Regression Results*

TABLE 5

Results of the Negative Binomial Regression Model

Dep. Variable: Model: Model Family: Link Function: Method: Date: Time: No. Iterations: Covariance Type:	Total_Deaths GLM NegativeBinomial Log IRLS Sun, 11 Aug 2024 17:59:48 8		No. Observations: Df Residuals: Df Model: Scale: Log-Likelihood: Deviance:		1176 1163 12 1.0000 -2331.6 392.56 287. 0.2596	
	coef	std err	z	P>IzI	[0.025	0.97
Intercept	-15.7573	38.52	-0.409	0.683	-91.272	59.7
DAY[T.MONDA	-0.0915	0.135	-0.680	0.497	-0.355	0.1
DAY[T.SATURD	0.1147	0.131	0.877	0.381	-0.142	0.3
DAY[T.SUNDA	0.1241	0.131	0.950	0.342	-0.132	0.3
DAY[T.THURSD	-0.0688	0.135	-0.510	0.610	-0.333	0.1
DAY[T.TUESDA	-0.0905	0.136	-0.667	0.505	-0.356	0.1
DAY[T.WEDNE	-0.1139	0.136	-0.840	0.401	-0.380	0.1

HOUR	0.0117	0.005	2.188	0.029	0.001	0.0
YEAR	0.0078	0.019	0.409	0.682	-0.030	0.0
Driver	0.3646	0.022	16.375	0.000	0.321	0.4
Pedestrian	0.4439	0.121	3.664	0.000	0.206	0.6
Vehicle_Defect	0.5871	0.325	1.807	0.071	-0.050	1.2
Pedal_Cyclists	0.4914	0.147	3.331	0.001	0.202	0.7

Table 5: Results of the Negative Binomial Regression Model

4.10 Extraction of Performance Matrix

Deviance: 392.56067409318524
pearson chi-Squared: 287.0218210199059
AIC: 4689.167006904877
BIC: -7829.702937304135
Log-Likelihood: -2331.5835034524384

Table 6: Results of Performance Matrix

According to the Pearson Chi-Squared and Deviance statistics, the model fits data fairly well.With the BIC being highly favorable (since it is negative), the AIC and BIC imply that the model's complexity may not be unduly penalized.while they compute the likelihood that the observed data fits the model. An increased log-likelihood that is nearer to 0 signifies a superior fit, The Log-Likelihood indicates that the model could be refined, but it is not a poor fit overall.

4.11 Model Validity

Coefficients and P-values for cause of Death:

	Coefficient	P-value
Driver	0.364551	2.863630e-60
Pedestrian	0.443879	2.486160e-04
Pedal_Cyclists	0.491388	8.638008e-04
Vehicle_Defect	0.587121	7.078982e-02

Table 7: Results of the Model's Validity

The coefficients in a regression model represent the expected change in the logarithm of the outcome (in this case, fatalities) in the event that the predictor variable changes by one unit and all other variables remain unchanged. Since this is a negative binomial regression, the coefficients indicate the multiplicative effect on the expected count of fatalities.

4.12 Driver (Coefficient = 0.3646, p-value ≈ 0)

The coefficient of 0.3646 suggests that an increase in driver-related issues (such as reckless driving, speeding, etc.) increases the expected count of fatalities by approximately 36.5% (since e^0.3646≈1.44, meaning a 44% increase) when all other factors are held constant.

The p-value is extremely small (2.86e-60), indicating that this variable is highly statistically significant in predicting fatalities. There is no chance that this relationship is due to random chance.

4.13 Pedestrian (Coefficient = 0.4439, p-value = 0.000248)

The coefficient of 0.4439 indicates that pedestrian-related factors (e.g., not using zebra ceossings , Fly overs , not using crosswalks) increase the expected number of fatalities by approximately 44.4% (since e^0.4439≈1.56e, meaning a 56% increase) when other factors remain constant.The p-value (0.000248) is very small, showing that this is a statistically significant predictor of fatalities. There's a high confidence that pedestrian-related incidents have a meaningful impact on the fatality rate.

4.14 Pedal Cyclists (Coefficient = 0.4914, p-value = 0.000864)

The coefficient of 0.4914 implies that accidents involving pedal cyclists are associated with a 49.1% increase in the expected count of fatalities (since e^0.4914 ≈1.63, or a 63% increase).The p-value (0.000864) is small, indicating that this variable is also statistically significant, with pedal cyclist-related accidents having a clear impact on the fatality count.

4.15 Vehicle Defect (Coefficient = 0.5871, p-value = 0.0708)

The coefficient of 0.5871 indicates that vehicle defects (e.g., brake failures, tire blowouts) contribute to a 58.7% increase in the expected fatality count (since $e^{0.5871} \approx 1.80$, an 80% increase), making it the most impactful factor among the ones listed.However, the p-value (0.0708) is slightly above the conventional significance level of 0.05, meaning that while vehicle defects appear to have a strong effect, the evidence is not quite strong enough to definitively assert that this is a significant predictor of fatalities. It's on the borderline of being statistically significant.

CHAPTER FIVE: DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

5.0 Introductions

This section highlights the findings of the study, focusing on the conclusions made and it also focuses on the challenges faced during the study and the proposed future studies that could enhance the safety of Kenyan citizens on the road and the effects of the causes of road accidents and policies put in place

5.1 Conclusion

Using data from the NTSA that was made available to the public, the study examined the nation's traffic situation for the months of January 2017 through December 2023. The data was broadly categorized into two types: fatal reports and daily reports. The fatal report data focused on analyzing the types of police-reported incidents to determine the general causes of fatalities using a negative binomial regression model. Meanwhile, the daily reports were examined for trends and other informative parameters.

This analysis offers a five-year overview of the current state of road traffic accidents (RTAs) in Kenya based on available data. The goal was to identify trends in the occurrence and severity of RTAs and assess the measures being implemented to address this persistent issue. Despite the significant impact of RTAs (Walugembe et al., 2020), the literature reveals that research on this subject has been limited over the past five years. In this study, the negative regression binomial model was used to analyze accident descriptions and identify key causes of fatalities. The results highlighted four primary causes: victims being knocked down, hit-and-run incidents, vehicles losing control, and head-on collisions, indicating that driver errors, which are preventable with appropriate interventions, are the predominant factors.

5.2 Summary of Findings

According to the results, creating a strong model is essential to successfully mitigating and preventing traffic accidents (RTAs). Because of the type of data involved, choosing a model that is both straightforward and efficient is important (Edward, 2023). In this study, the negative binomial model was chosen because the data exhibited over-dispersion. The study also discovered that there are a variety of factors that contribute to RTAs in Nairobi County, primarily falling into three categories: factors related to drivers, factors related to vehicles, and factors related to the roadway. Among these, driving-related issues, especially speeding, are the main contributors to collisions. In order to lower the risk of accidents and increase safety for all users of the road, policies should concentrate on changing the behavior of drivers (Keyvanfar, 2018).

The findings in Chapter 4 affirm key accident causation theories, such as Sociological, Cause, Domino, and Homeostasis, by highlighting pedestrian knockdowns, hit-and-run incidents, loss of vehicle control, and head-on collisions as leading causes of road fatalities in Kenya. This supports Sociological Theory, which suggests that cultural and social influences impact driving behavior, leading to differing responses and interpretations of road situations among diverse groups (Knoll et al., 2021). These differences in behavior often contribute to preventable driver errors, indicating that interventions targeting cultural perspectives and norms could reduce road accidents. Cause Theory further supports these findings by identifying driver errors and decision-making lapses as key factors in accidents, underscoring the need for proactive measures that address the root mistakes leading to these incidents (Sharma et al., 2017; Awal & Hasegawa, 2017).

Domino Theory also aligns with the data, as it views accidents as the result of sequential events triggered by unsafe actions, illustrated by incidents like hit-and-runs and pedestrian knockdowns. This chain-reaction concept supports multi-faceted intervention strategies aimed at breaking sequences of unsafe actions (Qalb et al., 2023). Finally, the Homeostasis Theory explains how drivers' perception of risk, confidence, and experience affect their behavior on the road, with certain high-risk actions potentially stemming from overconfidence or underestimation of danger. The combined findings indicate that an effective approach to reducing road traffic deaths in Kenya would be a comprehensive strategy that incorporates cultural awareness, behavioral interventions, and risk-perception adjustment among drivers.

5.3 Policy Intervention by the govt of Kenya

October 2003 saw the issuance of Legal Notice No. 161, which amended the Traffic Act Cap 403 by the Kenyan government's Ministry of Transport and Communications in an effort to address concerns regarding road safety (Muguro et al, 2022). This amendment mandated that all motor vehicles be equipped with seatbelts for every seating position. Driving without wearing a seatbelt became an offense under the Act, punishable by fines. This requirement applies to everyone in the vehicle, including the driver, and there is a fine for not fastening your seatbelt while driving (Hansson, 2022). Owners of Public Service Vehicles (PSVs) must also employ drivers and conductors on a permanent basis, offering monthly salaries instead of daily wages. This measure aimed to reduce the pressure on PSV crews to meet unrealistic daily targets, which often led to dangerous driving practices such as speeding, carrying excess passengers, and disregarding traffic rules (Business Daily, 2022).

Furthermore, vehicles with a tare weight exceeding 3,048 kilograms are required to have speed governors approved by the Minister for Transport, limiting their speed to no more than 80 km/h (The star, 2022). This measure was introduced to enhance passenger and pedestrian safety and to ensure drivers maintain full control of their vehicles. Additionally, PSVs must be painted with a yellow band on both sides, designed to make them easily identifiable and to prevent unauthorized vehicles from carrying passengers, which could increase accident risks (Muguro 2022). PSV owners are also required to display their names, addresses, registered routes, licensed passenger capacity, and tare weight on the vehicle. PSV drivers and conductors must wear uniforms and display special identification badges, with the driver's photograph clearly visible to all passengers (Traffic Act Cap 403).

Many studies have emphasized the importance of including pedestrian walkways and bicycle lanes in road design. It is crucial for the government, police, health professionals, and the public to be involved in creating preventive measures (Gossling et al., 2022). Road safety professionals should receive proper training to monitor the scale and impact of road traffic accidents (RTAs) in Nairobi County, addressing the lack of reliable data caused by inadequate data management skills (Kipchirchir, 2023). Urban planning should consider all road users and focus on behaviors and environmental settings. Law enforcement officers should also receive training on key aspects of road safety to strengthen preventive efforts (Mchawe et al., 2021).

5.4 Contributions of the Study

The study makes several original contributions to understanding and predicting road traffic deaths in Nairobi, particularly by identifying key factors influencing accident rates, developing a predictive model, and validating it within the local context. First, it establishes the specific causes of road fatalities—such as pedestrian knockdowns, hit-and-run incidents, loss of vehicle control, and head-on collisions—which provides detailed insights into the main contributors to road accidents in Nairobi. These findings enable targeted intervention strategies, such as pedestrian safety measures and driver behavior regulations, which can directly address local road safety challenges. Furthermore, the study's development of a Negative Binomial Regression model specifically tailored to Nairobi's accident data allows for a nuanced prediction of road traffic death rates under varying conditions. This predictive model is customized for the overdispersed nature of accident data and offers actionable insights for city planners and policymakers seeking to proactively manage traffic safety.

From a theoretical perspective, the study contributes to existing accident causation theories by confirming that cultural, behavioral, and sequential factors all play significant roles in traffic incidents in Nairobi. The study's findings reinforce Sociological Theory by showing that cultural traits influence driver behavior, which in turn impacts road safety outcomes, particularly within a diverse urban setting (Elander et al., 1993). The validation of Cause Theory and Domino Theory through local accident patterns also expands their application, suggesting that driver errors and sequential accident chains can be mitigated through targeted safety interventions. Additionally, the study enhances Homeostasis Theory by demonstrating that drivers' perception of risk and confidence significantly affect accident likelihood, thus highlighting the need for interventions that address risk awareness and behavioral adjustments (Kita et al., 2022).

5.5 Limitations of the study

The study faced significant challenges related to the availability and scarcity of data. Publicly accessible reports have been decreasing annually, and as mentioned earlier, the available data is often underreported, failing to capture the full scale of road accidents (World Health Organization, 2022). Reliable records are crucial for evaluating the health, financial, and social impacts of traffic accidents. Accurate data is vital for effective risk assessment, developing and evaluating interventions, and raising public awareness about road safety (Heydari, 2019).

Given the data challenges, it is recommended that NTSA (National Transport and Safety Authority) should make accident data publicly available on a regular basis, such as monthly. This would enable researchers, policymakers, and stakeholders to monitor trends, assess progress, and design effective prevention strategies. However, the current reports are limited in scope, often including only, victim details, accident locations, and victim categories. This information is insufficient for drawing comprehensive conclusions or conducting in-depth accident analysis (Muguro et al., 2022).

NTSA should consider expanding the scope of accident-related data to enable more detailed assessments. Essential information such as weather conditions, road intersections, driver characteristics (e.g., age, intoxication, or speeding), and vehicle types should be included. The parameters that researchers use for statistical modeling and inference are in line with this recommendation (Aldred et al., 2020; D. Wang et al., 2019; Yousefzadeh-Chabok et al., 2016In accordance with international standards, data reporting should also be standardized. This includes classifying road traffic deaths (RTDs) as deaths that occur within 30 days of the accident.

The research was unable to determine whether specific policy interventions, such as introducing breathalyzer tests (alco-blow) or adjusting travel times, have contributed to reducing road traffic accidents. The study focused on Nairobi, and due to unique factors such as the rate of urban population, and level of infrastructure development, the findings may not be universally applicable, leading to some variations when applied to different contexts.

5.6 Recommendations for Future Research

These findings of the study highlight the necessity for targeted road safety measures that focus not only on driver behavior but also on pedestrian safety, cyclist infrastructure, and vehicle maintenance. According to (Oviedo, 2019) there exists a considerable gap in research that links driver behavior with sustainable development and road safety. Evidence-based studies can inform policy decisions, demonstrating how interventions aimed at improving driver behavior can lead to a reduction in accidents and enhance socioeconomic outcomes (Bates, 2019). Research should not only identify existing issues but also evaluate the effectiveness of various interventions. In Africa, the lack of data hampers progress, highlighting the need for comprehensive databases and the use of advanced statistical analysis and modeling to bolster road safety initiatives (Jourbert et al., 2023).

Concerns concerning the efficacy and capacity of driving schools are also raised by the findings. Too few people and too few resources allow many of these institutions to offer high-quality instruction. Furthermore, because of a lack of driving test examiners, the rigor of the exam is frequently lacking, making it easy for even candidates with low qualifications to pass (Siregar, 2018). Programs for driver training need to be reorganized. While much focus is placed on the training of public service vehicle (PSV) drivers, the training for smaller vehicle operators is equally inadequate. Many trainees leave driving schools without the necessary skills to drive independently. Thus, there is a need for standardized training and thorough inspections of driving schools (Canser, 2019). The government should also establish and enforce vehicle standards through regular inspections, develop training curricula for drivers, traffic law enforcement agents, and other road users, and create a regulatory framework to enhance public awareness (Otieno, 2022).

In order to guarantee accuracy and turn these reports into useful information for addressing road safety issues, the investigation and reporting of traffic fatalities should also be reinforced (Green, 2022). The policymakers who require police data collection in order to formulate effective responses to road safety issues are currently disconnected from it. It is critical to comprehend the number of traffic fatalities, injuries, and accidents as well as the types of road users most impacted, the geographic areas where issues are most common, the risk factors that contribute to these problems, and the current state of road safety policies and programs. In addition to being useful, intermediate outcome measures like average speeds and the percentage of people who wear seat belts and helmets can be obtained with simple surveys (Heydari, 2019). It is crucial to involve different stakeholders, including the larger community. Establishing and sustaining national road safety initiatives requires cooperation, communication, and awareness. Prominent political figures who actively promote road safety, like the president or vice president, will help national initiatives gain traction (Kenya Road Safety Action Plan, 2024).

The reasons behind Kenya's adoption of particular response strategies, the conditions supporting or impeding these strategies, or the connection between the selected strategies and the temporary decline in traffic accidents were all the subject of scant analysis. Subsequent research endeavours should investigate the rationale behind Kenya's decision to employ specific response tactics and the factors that facilitate or impede such actions. (Otieno, 2022).

REFERENCES

Abegaz, T., & Gebremedhin, S. (2019). The magnitude of road traffic accident-related injuries and fatalities in Ethiopia. PloS one, 14(1), e0202240.

Abbas, Q., & Alsheddy, A. (2020). Driver fatigue detection systems using multi-sensors, smartphone, and cloud-based computing platforms: a comparative analysis. Sensors, 21(1), 56.

Adeleke, R., Osayomi, T., & Iyanda, A. E. (2020). Geographical patterns and effects of human and mechanical factors on road traffic crashes in Nigeria. International journal of injury control and safety promotion, 28(1), 3-15.

Adanu, E. K., Hu, Q., Liu, J., & Jones, S. (2021). Better rested than sorry: data-driven approach to reducing drowsy driving crashes on interstates. Journal of transportation engineering, Part A: Systems, 147(10), 04021067.

Afghari, A. P., Haque, M. M., Washington, S., & Smyth, T. (2019). Effects of globally obtained informative priors on Bayesian safety performance functions developed for Australian crash data. Accident Analysis & Prevention, 129, 55-65.

Aga, M. A., Woldeamanuel, B. T., & Tadesse, M. (2021). Statistical modelling of numbers of human deaths per road traffic accident in the Oromia region, Ethiopia. PloS one, 16(5), e0251492.

Ahmed, S. K., Mohammed, M. G., Abdulqadir, S. O., El-Kader, R. G. A., El-Shall, N. A., Chandran, D., ... & Dhamma, K. (2023). Road traffic accidental injuries and deaths: A neglected global health issue. Health science reports, 6(5), e1240.

Arsen . (2022, February 9). Researchers decry gaps in road accidents data in Kenya. The Star . Retrieved February 14, 2024, from https://www.the-star.co.ke/news/2022-02-09-researchers-decry-gaps-in-road-accidents-data-in-kenya/

Al-Madani, H. M. (2019). Analysis of past and future continental crash mortality rates employing long-term data. Journal of Transportation Safety & Security, 11(5), 464-490.

Alahmari, M. D., Alanazi, T. M., Batawi, A. A., Al-Osaimi, E. A., Alrabeeah, S., Jebakumar, Z., ... & BaHammam, A. S. (2019). Sleepy driving and risk of obstructive sleep apnea among truck drivers in Saudi Arabia. Traffic injury prevention, 20(5), 498-503.

Aldred, R., Goodman, A., Gulliver, J., & Woodcock, J. (2018). Cycling injury risk in London: A case-control study exploring the impact of cycle volumes, motor vehicle volumes, and road characteristics including speed limits. Accident Analysis & Prevention, 117, 75-84.

Ali[1], A. A. H. A. R., & Elhassan, A. A. A scientific study to determine the level of traffic safety application in Khartoum State-Sudan.

Aljaban, M. (2021). Analysis of car accidents causes in the usa.

Alonso, F., Esteban, C., Useche, S., & Colomer, N. (2018). Effect of road safety education on road risky behaviors of Spanish children and adolescents: findings from a national study. International journal of environmental research and public health, 15(12), 2828.

Af Wåhlberg, A. E., & Dorn, L. (2024). The effects of Electronic Stability Control (ESC) on fatal crash rates in the United States. Journal of safety research, 88, 217-229.

Antipova, A., & Antipova, A. (2018). Urban Environment: The Differences between the City in Europe and the United States. Urban Environment, Travel Behavior, Health, and Resident Satisfaction, 35-117.

Awal, Z. I., & Hasegawa, K. (2017). A study on accident theories and application to maritime accidents. Procedia engineering, 194, 298-306

Azevedo, M. J., & Azevedo, M. J. (2017). The state of health system (s) in Africa: challenges and opportunities. Historical perspectives on the state of health and health systems in Africa, volume II: the modern era, 1-73.

Azami-Aghdash, S., Moosavi, A., Gharaee, H., Sadeghi, G., Mousavi Isfahani, H., Ghasemi Dastgerdi, A., & Mohseni, M. (2021). Development of quality indicators to measure pre-hospital emergency medical services for road traffic injury. BMC health services research, 21, 1-12.

Baccini, A., & Petrovich, E. (2023). A global exploratory comparison of country self-citations 1996-2019. Plos one, 18(12), e0294669.

Bachani, A., Peden, M., Gururaj, G., Norton, R., & Hyder, A. (2017). Road traffic injuries.

Bates, L., Larue, G. S., Filtness, A. J., & Hawkins, A. (2019). Simulators, driver education and disadvantaged groups: A scoping review. Journal of the Australasian College of Road Safety, 30(4), 26-40.

Bhuiyan, M. R. H., Chowdhury, M. R. I., & Nokshi, K. N. (2021). Factors affecting safety perception of helmet and seat belt use: a bayesian network approach (Doctoral dissertation, Department of Civil and Environment Engineering, Islamic University of Technology (IUT), Board Bazar, Gazipur, Bangladesh).

Bellis, M. A., Hughes, K., Ford, K., Rodriguez, G. R., Sethi, D., & Passmore, J. (2019). Life course health consequences and associated annual costs of adverse childhood experiences across Europe and North America: a systematic review and meta-analysis. The Lancet Public Health, 4(10), e517-e528.

Belle, V., & Papantonis, I. (2021). Principles and practice of explainable machine learning. Frontiers in big Data, 4, 688969.

Bogos, K., Kiss, Z., Kerpel Fronius, A., Temesi, G., Jenő, E., Madurka, I., ... & Moldvay, J. (2021). Different trends in excess mortality in a central European country compared to main European regions in the year of the COVID-19 pandemic (2020): a Hungarian analysis. Pathology and Oncology Research, 27, 1609774.

Box, G. E. (1976). Time series analysis forecasting and control (Revised Ed.). Oakland, California: Holden-Day, Inc.

Box GEP, J. G. (2016). Time series analysis. In forecasting and control (pp. 179–209). New Jersey: Academic.

Carter, I. (2017). Human behavior in the social environment: A social systems approach. Routledge.

Casado-Sanz, N., Guirao, B., & Attard, M. (2020). Analysis of the risk factors affecting the severity of traffic accidents on Spanish crosstown roads: The driver's perspective. Sustainability, 12(6), 2237.

Cassarino, M., & Murphy, G. (2018). Reducing young drivers' crash risk: Are we there yet? An ecological systems-based review of the last decade of research. Transportation research part F: traffic psychology and behaviour, 56, 54-73.

Casner, S. M., & Hutchins, E. L. (2019). What do we tell the drivers? Toward minimum driver training standards for partially automated cars. Journal of cognitive engineering and decision making, 13(2), 55-66.

Cetin, V. R., Yilmaz, H. H., & Erkan, V. (2018). The impact of increasing speed limit in Turkey: The case of Ankara-Sivrihisar road section. Case Studies on Transport Policy, 6(1), 72-80.

Contreras, J., Espinola, R., Nogales, F. J., & Conejo, A. J. (2003). ARIMA models to predict next-day electricity prices. IEEE transactions on power systems, 18(3), 1014-1020.

COST329. (2004). Models for traffic and safety development. In the Final Report of The Action. Luxembourg: European Commission.

Chen, S., Kuhn, M., Prettner, K., & Bloom, D. E. (2019). The global macroeconomic burden of road injuries: estimates and projections for 166 countries. The Lancet Planetary Health, 3(9), e390-e398.

Chen, W. E. I., Hribar, P., & Melessa, S. (2018). Incorrect inferences when using residuals as dependent variables. Journal of Accounting Research, 56(3), 751-796.

Cheng, W., Gill, G. S., Ensch, J. L., Kwong, J., & Jia, X. (2018). Multimodal crash frequency modeling: Multivariate space-time models with alternate spatiotemporal interactions. Accident Analysis & Prevention, 113, 159-170.

Chicco, D., Warrens, M. J., & Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. PeerJ Computer Science, 7, e623.

Cholo, W., Odero, W., & Ogendi, J. (2023). The burden of motorcycle crash injuries on the public health system in Kisumu City, Kenya. Global Health: Science and Practice, 11(1).

Darzi, A., Gaweesh, S. M., Ahmed, M. M., & Novak, D. (2018). Identifying the causes of drivers' hazardous states using driver characteristics, vehicle kinematics, and physiological measurements. Frontiers in neuroscience, 12, 568.

Dotse, J. E. K. (2019). Behavioural Predictors of Driver Crash Risks in Ghana (Doctoral dissertation, University of Sheffield).

Damania, Richard & Desbureaux, Sebastien & Scandizzo, Pasquale & Mikou, Mehdi & Gohil, Deepali & Said, Mohammed. (2019). When Good Conservation Becomes Good Economics: Kenya's Vanishing Herds. 10.1596/33083.

Demissie, M. (2017). Risk factors associated with serious and fatal road traffic accidents in Manzini City, Swaziland.

Ding, J., Tarokh, V., & Yang, Y. (2017). Bridging AIC and BIC: a new criterion for autoregression. IEEE Transactions on Information Theory, 64(6), 4024-4043.

Dubey, R. K., Sánchez–Vaquerizo, J. A., Dailisan, D., & Helbing, D. (2024). Cooperative adaptable lanes for safer shared space and improved mixed-traffic flow. Transportation Research Part C: Emerging Technologies, 166, 104748.

EDWARD, O. M. (2023). REGRESSION AND MACHINE LEARNING MODELS TO PREDICT THE GROWTH OF ROAD TRAFFIC ACCIDENTS IN UGANDA (Doctoral dissertation, CAVENDISH UNIVERSITY UGANDA).

Eckersley, William & Salmon, Ruth & Gebru, Mulugeta. (2010). Khat, driver impairment and road traffic injuries: A view from Ethiopia. Bulletin of the World Health Organization, 88, 235-6. 10.2471/BLT.09.067512.

Ezenwa, A. O., Eseadi, C., Okide, C. C., Akubue, B. N., Nwankwo, M. J., Chukwuorji, J. C., & Ugwoke, S. C. (2018). Road traffic injuries in Nigeria: A cross-sectional study on prevalence, predictors, and road safety practices. Traffic Injury Prevention, 19(7), 706-712.

Elander, J., West, R., & French, D. (1993). Behavioral correlates of individual differences in road-traffic crash risk: An examination of methods and findings. Psychological bulletin, 113(2), 279.

Farhath, Z. A., Arputhamary, B., & Arockiam, L. (2016). A survey on ARIMA forecasting using time series model. Int. J. Comput. Sci. Mobile Comput, 5, 104-109.

Fu, G., Xie, X., Jia, Q., Li, Z., Chen, P., & Ge, Y. (2020). The development history of accident causation models in the past 100 years: 24Model, a more modern accident causation model. Process Safety and Environmental Protection, 134, 47-82.

Gathecha, G. K., Githinji, W. M., & Maina, A. K. (2017). Demographic profile and pattern of fatal injuries in Nairobi, Kenya, January–June 2014. BMC Public Health, 17, 1-7.

Gelderblom, A. J. (2021). Analysis of the relationship between the severity of road traffic crashes and the human factors involved: N4 Toll route case study (Doctoral dissertation, Stellenbosch: Stellenbosch University).

Gogolev, S., & Ozhegov, E. (2023). Asymmetric loss function in product-level sales forecasting: An empirical comparison. Applied Econometrics, 70, 109-121.

Gujarati, D. N., & Porter, D. C. (1999). Essentials of econometrics (Vol. 2). Singapore: Irwin/McGraw-Hill.

Govender, P., & Sivakumar, V. (2020). Application of k-means and hierarchical clustering techniques for analysis of air pollution: A review (1980–2019). Atmospheric pollution research, 11(1), 40-56.

Gössling, S., & McRae, S. (2022). Subjectively safe cycling infrastructure: New insights for urban designs. Journal of transport geography, 101, 103340.

Green, J. A. (2021). Too many zeros and/or highly skewed? A tutorial on modelling health behaviour as count data with Poisson and negative binomial regression. Health Psychology and Behavioral Medicine, 9(1), 436-45

Green, M., Muir, C., Oxley, J., & Sobhani, A. (2022). Safe System in road safety public policy: A case study from Victoria, Australia. IATSS research, 46(2), 171-180.

Hammad, K. A., Mohammed, M. A., Barakat, A. A., & Abdullahi, A. M. (2021). Epidemiological profile of road traffic accidents in North Kordofan, Sudan,(Jun 2017 to Jan 2018). EPRA international journal of socio-economic and environmental outlook, 8(2), e314-e314.

Hansson, S. O. (2022). Liberty, paternalism, and road safety. In The Vision Zero Handbook: Theory, Technology and Management for a Zero Casualty Policy (pp. 205-242). Cham: Springer International Publishing.

Han, H., Kim, S., Choi, J., Park, H., Yang, J. H., & Kim, J. (2021). Driver's avoidance characteristics to hazardous situations: A driving simulator study. Transportation research part F: traffic psychology and behaviour, 81, 522-539.

Hayes, & Stapleton. (2023, September 23). [Autoregressive Integrated Moving Average (ARIMA) Predictive Model]. Investopedia. Retrieved October 16, 2023, from https://www.investopedia.com/terms/a/autoregressive-integrated-moving-average-arima.asp#:~:text=An%20autoregressive%20integrated%20moving%20average%2C%20or%20ARIMA%2C%20is%20a%20statistical,values%20based%20on%20past%20values.

Heydari, S., Hickford, A., McIlroy, R., Turner, J., & Bachani, A. M. (2019). Road safety in low-income countries: state of knowledge and future directions. Sustainability, 11(22), 6249.

Hordofa, G. G., Assegid, S., Girma, A., & Weldemarium, T. D. (2018). Prevalence of fatality and associated factors of road traffic accidents among victims reported to Burayu town police stations, between 2010 and 2015, Ethiopia. Journal of Transport & Health, 10, 186-193.

Huh, H. S., & Park, C. Y. (2018). Asia-Pacific regional integration index: Construction, interpretation, and comparison. Journal of Asian Economics, 54, 22-38.

Hu, L., Zhou, X., Zhang, X., Wang, F., Li, Q., & Wu, W. (2021). A review on key challenges in intelligent vehicles: Safety and driver-oriented features. IET Intelligent Transport Systems, 15(9), 1093-1105.

Islam, M. R., Khan, M. M. A., Hossain, M. M., Mani, K. K., & Min, R. M. (2020). Road traffic accidents in Bangladesh: Why people have poor knowledge and awareness about traffic rules?. International journal of critical illness and injury science, 10(2), 70.

Islam, N., Shkolnikov, V. M., Acosta, R. J., Klimkin, I., Kawachi, I., Irizarry, R. A., ... & Lacey, B. (2021). Excess deaths associated with covid-19 pandemic in 2020: age and sex disaggregated time series analysis in 29 high income countries. bmj, 373.

Ihueze, C. C., & Onwurah, U. O. (2018). Road traffic accidents prediction modelling: An analysis of Anambra State, Nigeria. Accident analysis & prevention, 112, 21-29.

Jayan, K., & Muruganantham, B. (2021). Advanced Driver Assistance System technologies and its challenges toward the development of autonomous vehicle. In Intelligent Computing and Applications: Proceedings of ICICA 2019 (pp. 55-72). Springer Singapore.

Janmohammed, A. M. (2018). Unpacking road safety at a district level case of Cape Town, South Africa (Master's thesis, University of Cape Town).

Jianming Ma Bayesia," Multivariate Poisson Regression for Models of Injury count, by Severity". Transportation Research Record 1782.

Joubert, A., Murawski, M., & Bick, M. (2023). Measuring the big data readiness of developing countries–index development and its application to Africa. Information Systems Frontiers, 25(1), 327-350.

James, S. L., Lucchesi, L. R., Bisignano, C., Castle, C. D., Dingels, Z. V., Fox, J. T., ... & Mokdad, A. H. (2020). Morbidity and mortality from road injuries: results from the Global Burden of Disease Study 2017. Injury prevention, 26(Suppl 2), i46-i56.

Kassam, F., & Merali, H. (2019). Addressing Road Traffic Injuries in Low-and Middle-Income Countries: A Kingdon Policy Analysis.

Kaiser, N., & Barstow, C. K. (2022). Rural transportation infrastructure in low-and middle-income countries: a review of impacts, implications, and interventions. Sustainability, 14(4), 2149.

Keyvanfar, A., Shafaghat, A., Muhammad, N. Z., & Ferwati, M. S. (2018). Driving behaviour and sustainable mobility—policies and approaches revisited. Sustainability, 10(4), 1152.

Kinyanjui , M. k. (2023, January 18). 4,690 people died in road accidents in 2022 – report. https://www.the-star.co.ke/news/2023-01-18-4690-people-died-in-road-accidents-in-2022-report/.

Kinyanjui , M. K. (2024, February 13). Saturday was most dangerous day to travel in 2023 – NTSA. The Star

Kimani, S., Kabiru, C. W., Muteshi, J., & Guyo, J. (2020). Exploring barriers to seeking health care among Kenyan Somali women with female genital mutilation: a qualitative study. BMC international health and human rights, 20, 1-12.

Kipchirchir, K. K. (2023). Infrastructure Design on Road Safety Along Outering Roads in Nairobi City County, Kenya (Doctoral dissertation, KENYATTA UNIVERSITY).

Kita, E., Luria, G., Pindek, S., Albert, G., & Lotan, T. (2022). The use of risk homeostasis theory to reduce smartphone use during low-speed driving. Accident Analysis & Prevention, 168, 106596.

Khayesi, M. (2020). Vulnerable road users or vulnerable transport planning?. Frontiers in sustainable cities, 2, 543930.

Khan, K., Zaidi, S. B., & Ali, A. (2020). Evaluating the nature of distractive driving factors towards road traffic accident. Civil Engineering Journal, 6(8), 1555-1580.

Kock, R. A., Orynbayev, M., Robinson, S., Zuther, S., Singh, N. J., Beauvais, W., ... & Milner-Gulland, E. J. (2018). Saigas on the brink: Multidisciplinary analysis of the factors influencing mass mortality events. Science advances, 4(1), eaao2314.

Knoll, M., Götz, M., Adriasola, E., Al-Atwi, A. A., Arenas, A., Atitsogbe, K. A., ... & Zacher, H. (2021). International differences in employee silence motives: Scale validation, prevalence, and relationships with culture characteristics across 33 countries. Journal of Organizational Behavior, 42(5), 619-648.

Large, D. R., Kim, H., Merenda, C., Leong, S., Harvey, C., Burnett, G., & Gabbard, J. (2019). Investigating the effect of urgency and modality of pedestrian alert warnings on driver acceptance and performance. Transportation research part F: traffic psychology and behaviour, 60, 11-24.

Land, K. C., McCall, P. L., & Nagin, D. S. (1996). A comparison of Poisson, negative binomial, and semiparametric mixed Poisson regression models: With empirical applications to criminal careers data. Sociological Methods & Research, 24(4), 387-442.

Lavrenz, S. M., Vlahogianni, E. I., Gkritza, K., & Ke, Y. (2018). Time series modeling in traffic safety research. Accident Analysis & Prevention, 117, 368-380.

Li, L. C., & Mo, P. L. L. (Eds.). (2023). Hong Kong Professional Services and the Belt and Road Initiative: Challenges for Co-evolving Sustainability. Taylor & Francis.

Lin, W. C., & Tsai, C. F. (2020). Missing value imputation: a review and analysis of the literature (2006–2017). Artificial Intelligence Review, 53, 1487-1509.

Linardatos, P., Papastefanopoulos, V., & Kotsiantis, S. (2020). Explainable ai: A review of machine learning interpretability methods. Entropy, 23(1), 18.

Lowrie, J., & Brownlow, H. (2020). The impact of sleep deprivation and alcohol on driving: a comparative study. BMC public health, 20, 1-9.

Lord, S., Cloutier, M. S., Garnier, B., & Christoforou, Z. (2018). Crossing road intersections in old age—With or without risks? Perceptions of risk and crossing behaviours among the elderly. Transportation research part F: traffic psychology and behaviour, 55, 282-296.

McCarty, D., & Kim, H. W. (2024). Risky behaviors and road safety: An exploration of age and gender influences on road accident rates. PLoS one, 19(1), e0296663.

Manivasakan, H., Kalra, R., O'Hern, S., Fang, Y., Xi, Y., & Zheng, N. (2021). Infrastructure requirement for autonomous vehicle integration for future urban and suburban roads–Current practice and a case study of Melbourne, Australia. Transportation Research Part A: Policy and Practice, 152, 36-53.

Mykhailovska, N. S., Grytsay, A. V., Miniailenko, L. E., & Stetsyuk, I. O. (2018). The first aid in the case of non-epidemic diseases: study guide for the practical classes and individual work for 6th-years students of international faculty (speciality" General medicine") Discipline" General practice–family medicine".

Manyara, Charles. (2016). Combating Road Traffic Accidents in Kenya: A Challenge for an Emerging Economy. 10.1057/9781137574633_7.

Makuu, M. (2018). Socio-economic Consequences of Road Traffic Accidents to the Victims and their Families in Dar es Salaam Tanzania. Huria: Journal of the Open University of Tanzania, 25(2), 181-197.

Macharia, K. K. (2019). Modeling Fatalities Associated With Road Traffic Accidents And Other Factors Using Poisson Model (Doctoral dissertation, UoN).

Martin, J., De Adana, D. D. R., & Asuero, A. G. (2017). Fitting models to data: residual analysis, a primer. Uncertainty quantification and model calibration, 133.

Manoti, L. K. (2021). Exploring the facilitators and challenges of Emergency Medical Services: a case of Kisii County Government (Doctoral dissertation, Strathmore University).

Mahajan, K., & Velaga, N. R. (2021). Sleep-deprived car-following: Indicators of rear-end crash potential. Accident Analysis & Prevention, 156, 106123.

Mchawe, L. A. (2018). An Investigation of Road Accidents Casuality in Dar es Salaam: A Case of Reported Motor Vehicle Accidents in 2018 (Doctoral dissertation, The Open University of Tanzania).

Miccio, A. N. (2021). The Future of Third Avenue and the Gowanus Expressway: Planning for Pedestrians and Bicycles (Master's thesis, Pratt Institute).

Mittal, N. (2008). Policies and programs for road safety in developing India. Journal of Emergencies, Trauma, and Shock, 1(1), 42-49.

Morton, T. R. (2012). Neighborhood correlates of childhood injury: a case study of Toronto, Canada. University of Toronto (Canada).

Mohammed, A. A., Ambak, K., Mosa, A. M., & Syamsunur, D. (2019). A review of traffic accidents and related practices worldwide. The Open Transportation Journal, 13(1).

Mohammed, M., Abdullahi, A., & Barakat, A. (2023). Investigating of Risk Factors Associated with Exposure to Road Traffic Accidents among Drivers, El-Obeid, North Kordofan State, Sudan; A Cross-sectional Study.

Muguro, J., Sasaki, M., Matsushita, K., & Njeri, P. (2020). Trend analysis and fatality cause in Kenyan roads: A review of road traffic accident data between 2015 and 2020. Cogent Engineering, 7, 10.1080/23311916.2020.1797981.

Moturi, W. O. (2019). Three essays on opportunities and challenges in the transportation service industry of East Africa.

Montle, M. E., & Moleke, H. (2021). Exploring Human Factors that Contribute to Fatal Road Accidents in South Africa. African Journal of Development Studies (formerly AFFRIKA Journal of Politics, Economics and Society), 2021(si1), 97-118.

Mphela, T. (2020). Causes of road accidents in Botswana: An econometric model. Journal of Transport and Supply Chain Management, 14(1), 1-8.

Mpunzi, L. M. (2018). A Critical Analysis of the South African National Road Safety Strategies. University of Johannesburg (South Africa).

Mylonas, C., Mitsakis, E., & Kepaptsoglou, K. (2023). Criticality analysis in road networks with graph-theoretic measures, traffic assignment, and simulation. Physica A: Statistical Mechanics and its Applications, 629, 129197.

NAGABONA, S. (2023). Assessment of Preventive Measures for Motorcycle Road Accidents in Tanzania (Doctoral dissertation, IAA).

Neill, R. (2023). TRANSLATING CONTEXT-SPECIFIC FINDINGS INTO MIDDLE-RANGE INSIGHTS: EXAMPLES FROM REHABILITATION, ROAD SAFETY, AND INTEGRATION OF HEALTH CARE SERVICES (Doctoral dissertation, Johns Hopkins University).

Ngari, P. M. (2020). Prevalence and factors associated with commercial motorcycle accidents in embu County, Kenya (Doctoral dissertation, JKUAT-COHES).

Ndungu, Matayo, & Mwai. (2015, April). Analysis of Causes & Response Strategies of Road Traffic Accidents in Kenya. Dedan Kimathi University Repository. Retrieved October 16, 2023, from http://repository.dkut.ac.ke:8080/xmlui/bitstream/handle/123456789/259/Analysis%20of%20Causes%20%26%20Response%20Strategies%20of%20Road%20Traffic.pdf?sequence=1

Negussie, Y., Geller, A., Teutsch, S. M., & National Academies of Sciences, Engineering, and Medicine. (2018). Introduction and Context. In Getting to Zero Alcohol-Impaired Driving Fatalities: A Comprehensive Approach to a Persistent Problem. National Academies Press (US).

Naqvi, N. (2021). Modeling the effects of fuel price changes on road traffic collisions: evidence from the UK and the EU (Doctoral dissertation, Loughborough University).

Nikitas, A., Avineri, E., & Parkhurst, G. (2018). Understanding the public acceptability of road pricing and the roles of older age, social norms, pro-social values and trust for urban policy-making: The case of Bristol. Cities, 79, 78-91.

Nunn, J. (2021). Geodemographic profiling of culpable drivers to target road safety interventions in serious injury crashes (Doctoral dissertation, Loughborough University).

Ma, Q., Wan, M., Shao, J., Zhong, M., Guo, Y., & Wang, W. (2022). Six-hierarchy model of accident analysis and its application in coal mine accidents. Journal of safety science and resilience, 3(1), 61-71.

Makwaga, O., Adungo, F., Mokaya, T., Echoka, E., & Mwau, M. (2024). Opportunities and challenges on hospital preparedness to handle motorcycle accidents in Busia County, Kenya: an exploratory qualitative study. The Pan African Medical Journal, 47.

Odero, W., Khayesi, M., & Heda, P. M. (2013). Road traffic injuries in Kenya: Magnitude, causes, and status of intervention. Injury Control and Safety Promotion, 10(1-2), 53-61.

OTIENO, C. O. (2022). EFFECTS OF TRAFFIC LAW ENFORCEMENT ON REDUCTION OF ROAD ACCIDENTS IN KENYA: THE CASE OF SALGAA-MAU SUMMIT HIGHWAY.

Oviedo-Trespalacios, O., Truelove, V., Watson, B., & Hinton, J. A. (2019). The impact of road advertising signs on driver behaviour and implications for road safety: A critical systematic review. Transportation research part A: policy and practice, 122, 85-98.

Oluwadiya, K. S., Olakulehin, O. A., Adesunkanmi, A. R., & Olatoke, S. A. (2019). Pattern and outcome of road traffic injuries in Nigeria: An observational study. West African Journal of Medicine, 36(2), 137-143.

Oluwajana, S. D., Park, P. Y., & Cavalho, T. (2022). Macro-level collision prediction using geographically weighted negative binomial regression. Journal of Transportation Safety & Security, 14(7), 1085-1120.

Oloo Mc'opiyo, S. (2019). Traffic management and road safety in Kisumu County, South Western Kenya (Doctoral dissertation, Kampala International University, College of Humanities and social sciences.).

Osoro, A. A. (2024). Determinants of Road Traffic Accidents in Kenya.

Patriarca, R., Chatzimichailidou, M., Karanikas, N., & Di Gravio, G. (2022). The past and present of System-Theoretic Accident Model And Processes (STAMP) and its associated techniques: A scoping review. Safety science, 146, 105566.

Pashayev, E. (2023). Area-wide Traffic Calming in Inner-city Area of Dresden (Doctoral dissertation, Westsächsische Hochschule Zwickau).

Pawłowski, W., Goniewicz, K., Schwebel, D. C., Shen, J., & Goniewicz, M. (2019). Road traffic injuries in Poland: magnitude and risk factors. European journal of trauma and emergency surgery, 45, 815-820.

Paolella, M. S. (2018). Linear models and time-series analysis: regression, ANOVA, ARMA and GARCH. John Wiley & Sons.

Preez, Johann & Witt, Stephen. (2003). Univariate versus multivariate time series forecasting: An application to international tourism demand. International Journal of Forecasting, 19, 435-451. 10.1016/S0169-2070(02)00057-2.

Qalb, A., Arshad, H. S. H., Nawaz, M. S., & Hafeez, A. (2023). Risk reduction via spatial and temporal visualization of road accidents: a way forward for emergency response optimization in developing countries. International journal of injury control and safety promotion, 30(2), 310-320.

REPUBLIC OF KENYA MINISTRY OF TRANSPORT, INFRASTRUCTURE, HOUSING, URBAN DEVELOPMENT & PUBLIC WORKS STATE DEPARTMENT FOR INFRASTRUCTURE. (2022, November). /www.transport.go.ke.

Rithaa, G. K. (2023). Association Between Prehospital Emergency Care (Pec) Factors and Traumatic Brain Injury (Tbi) Mortality in Kiambu and Nairobi Counties, Kenya (Doctoral dissertation, University of Nairobi).

Rodney, W. (2018). How europe underdeveloped africa. Verso Books.

Sam, E. F., Blay, D. K., Antwi, S., Anaafi, C., & Adoma, J. A. (2019). Pre-hospital and trauma care to road traffic accident victims: experiences of residents living along accident-prone highways in Ghana. Emergency Medicine and Trauma, 10(34), 234-8.

Saari, U. (2019). Planning and design implications from traffic safety evaluation for tramway systems (Master's thesis).

Saayman, A., & Botha, I. (2015). Evaluating non-linear approaches in forecasting tourist arrivals. Economic Research Southern Africa. Tourism Economics, 23(3), 594-613.

Soathong, A., Wilson, D., Ranjitkar, P., & Chowdhury, S. (2019). A critical review of policies on pedestrian safety and a case study of New Zealand. Sustainability, 11(19), 5274

Soathong, A. (2023). Pedestrian safety at urban mid-block crossings (Doctoral dissertation, ResearchSpace@ Auckland).

Saxena. (2017, August). Analysis of Road Traffic Accidents using Causation Theory with Traffic Safety Model and Measures. International Journal for Research in Applied Science & Engineering Technology (IJRASET).

Schepers, P., Lovegrove, G., & Helbich, M. (2019). Urban form and road safety: Public and active transport enable high levels of road safety. Integrating human health into urban and transport planning: a framework, 383-408.

Shaon, M. R. R., Qin, X., Shirazi, M., Lord, D., & Geedipally, S. R. (2018). Developing a Random Parameters Negative Binomial-Lindley Model to analyze highly over-dispersed crash count data. Analytic methods in accident research, 18, 33-44.

Shen, N., & González, B. (2021). Bayesian information criterion for linear mixed-effects models. arXiv preprint arXiv:2104.14725.

Sharma, R., & Gupta, A. K. (2017). Safety Management and Hazards Control Measures in Construction.

"Seventy-Second Session General Assembly Resolution: Improving Global Road Safety A/RES/72/271," United Nations, accessed April 6, 2023, https://unece.org/DAM/

road_Safety/Documents/UN_Road_Safety_Trust_Fund_launch_event_April_2018/GA_resolution_A_RES_72_271_N1810643.pdf.

Sowada, C., Sagan, A., Kowalska-Bobko, I., Badora-Musiał, K., Bochenek, T., Domagała, A., ... & World Health Organization. (2019). Poland: health system review.

Siregar, A. A. (2018). How can speed enforcement be made more effective? An investigation into the effect of police presence, speed awareness training and roadside publicity on drivers' choice of speed (Doctoral dissertation, University of Leeds).

Sidumo, B., Sonono, E., & Takaidza, I. (2024). Count Regression and Machine Learning Techniques for Zero-Inflated Overdispersed Count Data: Application to Ecological Data. Annals of Data Science, 11(3), 803-817.

Tavakkoli, M., Torkashvand-Khah, Z., Fink, G., Takian, A., Kuenzli, N., de Savigny, D., & Cobos Muñoz, D. (2022). Evidence from the decade of action for road safety: a systematic review of the effectiveness of interventions in low and middle-income countries. Public health reviews, 43, 1604499.

Wang, X., Zhou, Q., Quddus, M., & Fan, T. (2018). Speed, speed variation and crash relationships for urban arterials. Accident Analysis & Prevention, 113, 236-243.

Wahab, L., & Jiang, H. (2019). A comparative study on machine learning-based algorithms for prediction of motorcycle crash severity. PLoS one, 14(4), e0214966.

Wen, X., Xie, Y., Jiang, L., Pu, Z., & Ge, T. (2021). Applications of machine learning methods in traffic crash severity modelling: current status and future directions. Transport reviews, 41(6), 855-879.

Wilde, G. J. (1982). The theory of risk homeostasis: implications for safety and health. Risk analysis, 2(4), 209-225.

World Health Organization. (2023, December 13). Despite notable progress, road safety remains an urgent global issue. World Health Organization.

World Health Organization. (2022). Decade of action for road safety 2011-2020: success stories from the Eastern Mediterranean Region.

World Health Organization. (2023). Pedestrian safety: a road safety manual for decision-makers and practitioners. World Health Organization.

Workie, M. S., & Azene, A. G. (2021). A bayesian zero-inflated regression model with application to under-five child mortality. Journal of big data, 8(1), 1-23.

Wu, P., Song, L., & Meng, X. (2021). Influence of built environment and roadway characteristics on the frequency of vehicle crashes caused by driver inattention: A comparison between rural roads and urban roads. Journal of safety research, 79, 199-210.

(n.d.). Timeseries Concepts. Retrieved October 16, 2023, from https://www.termpaperwarehouse.com/essay-on/Timeseries-Concepts/486103.

Walugembe, F., Levira, F., Ganesh, B., & Lwetoijera, D. W. (2020). A retrospective study on the epidemiology and trends of road traffic accidents, fatalities and injuries in three Municipalities of Dar es Salaam Region, Tanzania between 2014-2018. Pan African medical journal, 36(1).

Winkler, S., Kazazi, J., & Vollrath, M. (2018). How to warn drivers in various safety-critical situations–Different strategies, different reactions. Accident Analysis & Prevention, 117, 410-426.

Yasin, Y. J. (2023). FACTORS AFFECTING CHANGES IN ROAD TRAFFIC COLLISION RELATED INJURIES AND DEATHS OVER TIME: THE GLOBAL AND THE UNITED ARAB EMIRATES PERSPECTIVES.

Young, G. K. (2020). Seizing the Wheel: The Need for Uniformity in State Driving Bans for People with Epilepsy. Miss. LJ, 90, 839.

Yao, L., Chu, Z., Li, S., Li, Y., Gao, J., & Zhang, A. (2021). A survey on causal inference. ACM Transactions on Knowledge Discovery from Data (TKDD), 15(5), 1-46.

Ye, Z., Xu, Y., & Lord, D. (2018). Crash data modeling with a generalized estimator. Accident Analysis & Prevention, 117, 340-345.

Zamzuri, Z. H., Sapuan, M. S., & Ibrahim, K. (2018). The extra zeros in traffic accident data: A study on the mixture of discrete distributions. Sains Malaysiana, 47(8), 1931-1940.

Zhang, J., Yang, Y., & Ding, J. (2023). Information criteria for model selection. Wiley Interdisciplinary Reviews: Computational Statistics, e1607.

Ziakopoulos, A., & Yannis, G. (2020). A review of spatial approaches in road safety. Accident Analysis & Prevention, 135, 105323.

Zheng, L., Sayed, T., & Mannering, F. (2021). Modeling traffic conflicts for use in road safety analysis: A review of analytic methods and future directions. Analytic methods in accident research, 29, 100142.