ADDIS ABABA UNIVERSITY

COLLEGE OF TECHNOLOGY AND BUILT ENVIRONMENT

SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

Investigation of Heavy Truck Crash on Freight Transport Corridor (case study of Adama - Awash Road Segment)

A Thesis in Road and Transport Engineering

By Alelign Berihun

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A Thesis

Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science

The undersigned have examined the thesis entitled '**Investigation of Heavy Truck Crash on Freight Transport Corridor (case study of Adama - Awash Road Segment)**' presented by **Alelign Berihun**, a candidate for the degree of **Master of Science** and hereby certify that it is worthy of acceptance.

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Chair person	Signature	Date

UNDERTAKING

I certify that the research work titled "**Investigation of Heavy Truck Crash on Freight Transport Corridor (case study of Adama - Awash Road Segment)'**" is my work. The work has not been presented elsewhere for assessment. Where material has been used from other sources it has been properly acknowledged /referred.

Alelign Berihun

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ABSTRACT

Road traffic collisions remain a major global public health and transportation problem, with the burden particularly high in developing countries due to rapid motorization, mixed traffic, and infrastructure limitations. Heavy trucks, while essential for freight movement and economic growth, are frequently involved in severe crashes because of their size and weight. This study examines heavy truck crash severity and evaluates the safety performance of the 120 km Adama–Awash freight corridor, which carries about 90% of Ethiopia’s import export traffic and serves as a key link to the Djibouti port.

The study has employed ordinal logistic regression for crash severity analysis and negative binomial regression and Empirical Bayes (EB) method for frequency modeling for safety performance evaluation respectively. Secondary crash data for the period of five years (2019- 2023) were collected from Traffic Police, and Road geometric, AADT and pavement condition data were collected from a government office. Crash outcome was used as the dependent variable, while Driver Characteristics, Vehicle-Related Factors, Road Geometry and Pavement Conditions, and Environmental and Spatial Conditions were included as independent variables. Point Biserial correlation and collinearity diagnostics have also been determined to assess the relationships among the independent variables.

And the ordinal logistic regression model results indicate that younger drivers ((18–24 years)) (β = 0.824), drivers who has below 5 years’ experience (β = 0.6392,), articulated trailers trucks (β = 0.6082), Pedestrian crashes (β = 2.9614), head-on crashes (β = 2.4742,), and Rollover crashes (β = 1.2041), dry surfaces asphalt (β= 1.0426), Good weather condition ((β = 1.2141), drivers while moving straight (β= 1.0015) and overtaking (β= 1.35) has associated with severe crashes. Finally, road safety was assessed using Empirical Bayes (EB) weights and high-risk hotspots identified, and the results revealed that approximately 45–50% of the total corridor length performed worse than expected. severe crashes and higher crash frequency were mainly caused by factors related to drivers' behavior rather than environmental factors. Therefore, strengthened speed management, targeted enforcement, safety measures are recommended.

Key Words: OLR, Empirical Bayes (EB) method, Crash Severity Modeling

ACRONYMS AND ABBREVIATIONS

- AADT Annual Average Daily Traffic
- EB Empirical Bayes
- ERA Ethiopian Roads Administration
- EC Ethiopian calendar
- MLR Multinomial Logistic Regression.
- NB Negative Binomial regression
- IRI International Roughness Index
- OLR Ordinal Logistic Regression
- RTC Road traffic collision

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CAPTER ONE

INTRODUCTION

1.1. Background

Road traffic crashes continue to be a global problem. The World Health Organization (WHO) reported in its 2023 Global Status Report that such crashes cause close to 1.19 million fatalities annually and an estimated 50 million (WHO, 2023). The WHO further argues that this global phenomenon is expected to continue well into the future if current trends are maintained(WHO, 2023). Although the most frequent type of vehicle involved in crashes is automobiles, which contribute significantly to the overall magnitude and severity of crashes especially in urban areas heavy-duty trucks are involved in a higher rate of fatalities and more serious injuries per crash relative to cars and motorcycles. Additionally, crashes involving these heavier vehicles are likely to affect more people per crash. (Chand et al., 2024; Yan et al., 2021)

Surprisingly low and medium-income nations worldwide account for 92% of total road fatalities, while contributing only about 60% of the world's vehicles(Chandran et al., 2023).

Freight transport vehicles, particularly heavy trucks, represent a significant safety concern among the various types of vehicles. Road crashes related to freight transport are a common problem in developing and developed countries, although the extent, underlying causes, and consequences vary significantly. In developing countries, the high crash rates are commonly caused by lack of well-designed regulatory, infrastructure, and socioeconomic challenges. In contrast developed countries generally have more strict safety protocols in place leading to reduction in fatalities (Risdianto & Widyastuti, 2022; Shirazian, 2020)

In countries with less economic development, traffic crashes with freight transport trucks represent a major public safety concern, often leading to a high rate of severity outcome. The severity of these crashes is influenced by multiple factors including driver behavior (such as reckless or negligent driving), inadequate driver training, and the lack of advanced vehicle safety features, poor road design, and the prevalence of overloaded trucks, compounded by weak enforcement and inspection regime (Rahimi et al., 2020; Saad et al., 2021).

Although Ethiopia has low motor vehicle ownership of only one vehicle for every 92 persons the nation has high road traffic fatality rates per vehicle, and road safety is a significant public health issue. Countrywide surveys have estimated fatalities as much as 4,922 deaths per 100,000 vehicles, with road traffic crashes responsible for almost 44% of all crashes, deaths and disproportionately young adults, males, and vulnerable road users like pedestrians and motorcyclists (Abegaz & Gebremedhin, 2018; Denu et al., 2021a; Neki et al., 2022)

Figure 1 illustrates the death toll (deaths per 100,000 inhabitants). As shown in the figure, Ethiopia has high fatality rates.

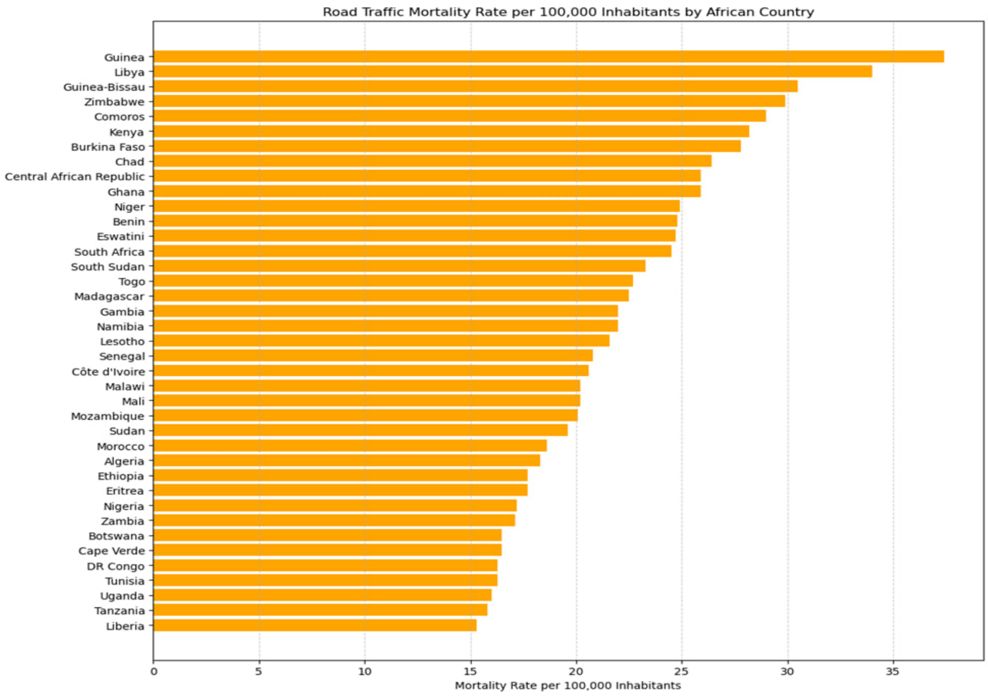

Figure 1: Death toll (death/10,000 licensed motor vehicles), Source: WHO, 2024 Report)

As per various studies drivers are the main cause of traffic crashes in Ethiopia and determined that a number of driver and vehicle factors were significant contributors to road traffic crashes (RTCs) (Zenu et al., 2023). Inexperienced drivers were 2.6 times more likely to be involved in crashes, drinking alcohol increased the probability of RTCs by a significant amount, with drivers being 5.17 times more at risk, lack of seat belt use also contributed, with drivers being 3.19 times more likely to be involved in crashes, furthermore older vehicles with more years of service were also linked to a 2.6 times greater risk of crashes. Speeding was another significant contributor, which increased the probability of RTCs by 4.59 times (Zenu et al., 2023).

Another researcher's study summarized that drivers commonly cause crashes by insufficient headway, failing to yield to pedestrians, turning in the wrong manner, and making wrong turns (Mamo et al., 2022). The primary driver faults are drunk driving, speeding, overloading, and driver fatigue. Traffic crashes most often involve male drivers, drivers with lower levels of education, experienced drivers, and older passenger cars. Deficiently designed and poorly maintained roads also contribute significantly to crashes (Meskele, 2024).

Another study highlights that key underlying factors of the problems have been identified as poor road conditions, lack of awareness about road safety, the existence of mixed types of traffic, ineffective legislation and poor enforcement mechanisms, poorly maintained vehicles, limited emergency medical services, and the lack of a law that enforces traffic crash insurance (Bulcha, 2024; Deme, 2019). As stated in the above the factors causing traffic crashes in the country can mainly classified into driver-related factors, vehicle-related factors, weather conditions, road conditions and lighting conditions (Eshetu, 2019).

But a five-year national traffic crash data (2012 EC–2016 EC; 2019/20–2023/24), collected from the Road Safety and Insurance Fund Service, show a decrease in crash frequency over the time period. The dataset includes traffic crash records collected from the regional administrations of Oromia, Amhara, Somali, Afar, Benishangul-Gumuz, Gambela, Harari, Sidama, South Ethiopia, Southwest Ethiopia, and Central Ethiopia. Due to the ongoing conflict in the Tigray region during the period, data from Tigray were not collected and are therefore excluded from this report. In addition, the self-governing cities of Addis Ababa and Dire Dawa are not included. Figure 2 and Table 1 below present the grand total of traffic crashes, representing the combined sum of all included regions for the time period 2019/20–2023/24, excluding Addis Ababa, Dire Dawa, and the Tigray Regional Administration.

Table 1: National Traffic Crash Trends in Ethiopia (2019/20–2023/24),

	Traffic crash of all regions				
Year	Death	Serious Injury	Slight Injury	Property Damage	Total
2012 EC (2019/20)	2807	1909	1159	2644	8519
2013 EC (2020/21)	2945	1834	1055	2778	8612
2014 EC (2021/22)	2700	1837	980	2525	8042
2015 EC (2022/23)	2588	1642	837	2681	7748
2016 EC (2023/24)	2257	1749	890	2418	7314

Source: Road Safety and Insurance Fund Service

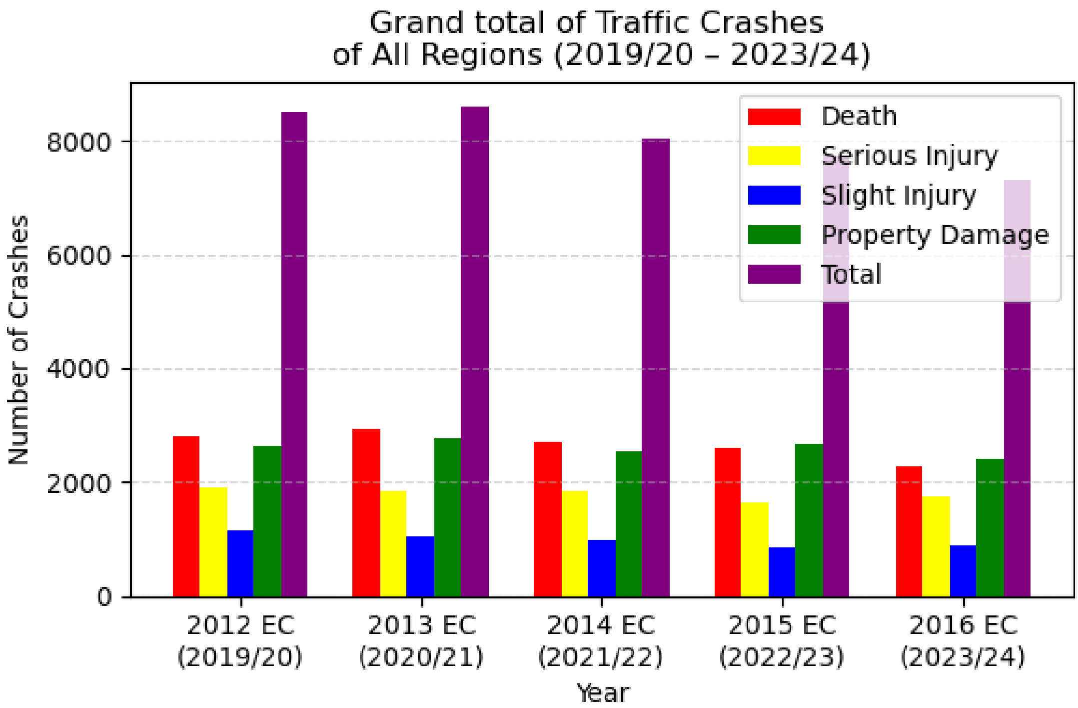

Figure 2: National Traffic Crash Trends in Ethiopia (2019/20–2023/24), Excluding Addis Ababa, Dire Dawa, and Tigray

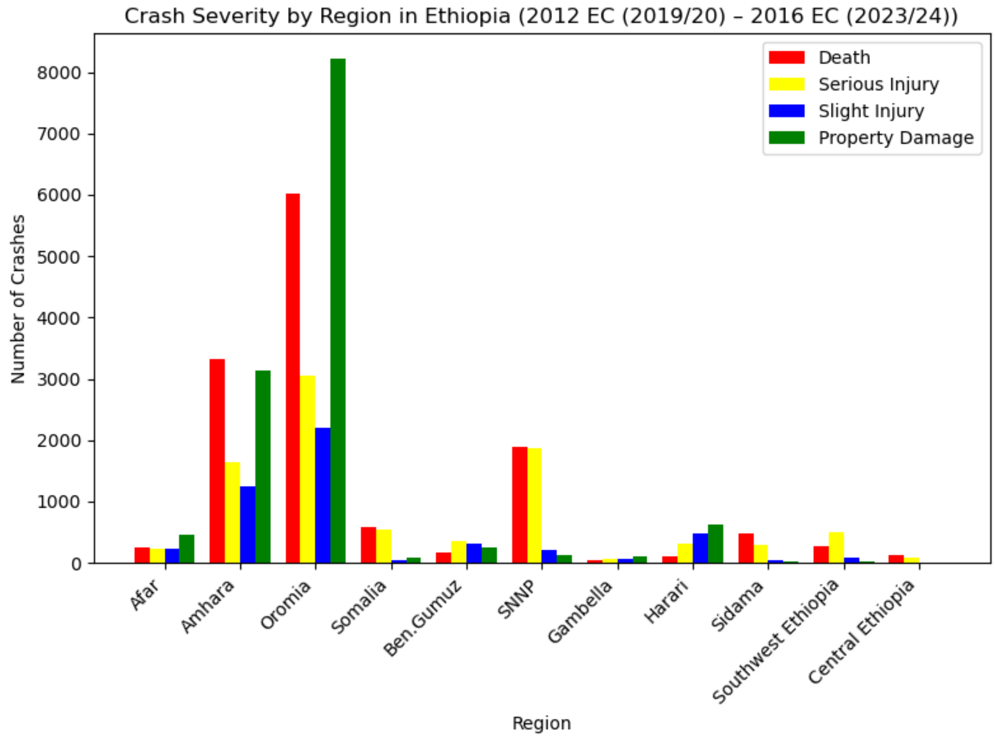

Figure 3: Crash Severity by Region in Ethiopia (2012 EC (2019/20) – 2016 EC (2023/24)

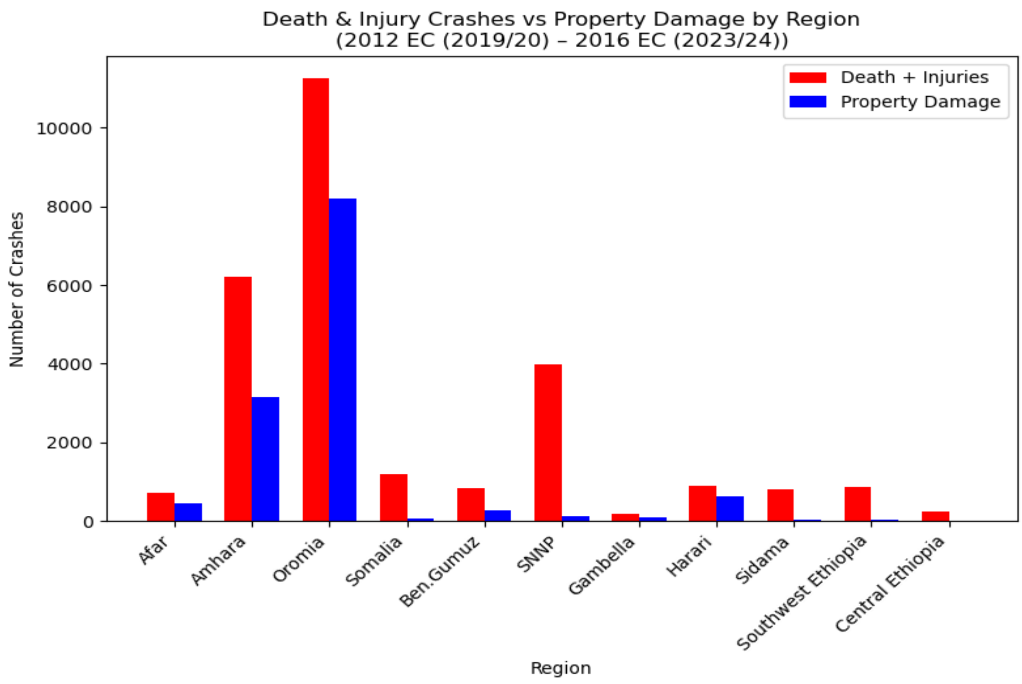

***Figure 4**: Death & Injury Crashes vs Property Damage by Region\n(2012 EC (2019/20) – 2016 EC (2023/24))*

Table 2*: National Distribution of Registered Vehicles by Regional Administration*

Region	Number of Registered Vehicles	Percentage Share (%)
Tigray	60,800	5.07
Afar	8,277	0.69
Amhara	106,434	8.87
Oromia	204,026	17.00
Somalia	19,579	1.63
B. Gumuz	10,655	0.89
S. N. N. P.	118,424	9.87
Gambella	6,237	0.52
Harari	10,728	0.89
Addis Ababa	630,440	52.53
Dire Dawa	24,510	2.04
Total	1,200,110	100.00

Source: The Reporter Magazine - Registered vehicle in Ethiopia , 2020

The five-year crash distribution by regional administration from 2019/20 to 2023/24 shows that the Oromia regional administration experiences a relatively high record in terms of severity and frequency. This is followed by the Amhara and SNNP regions, which also exhibit relatively high crash occurrence and severity. The observed pattern reflects variations in traffic exposure, road network characteristics, and regional mobility demands, underscoring the need for region-specific road safety interventions.

The highest crash record in Oromia regional administration can be associated with the fact that the region is the largest in terms of both area and population. In addition, as stated in the above Table 2 a reported data in back 2020 the total number of registered vehicles in Ethiopia was 1.2 million vehicles and Oromia accounts for 17% of registered vehicles nationwide, making it the region with the highest number of registered vehicles after Addis Ababa. The number of registered vehicles in the country reaches 1.6 million in 2025 as reported by Birr metrics (LCA, 2024), a digital news platform based in Addis Ababa. This high level of vehicle ownership, combined with its strategic location, which surrounds and is closely connected to Addis Ababa, and extensive road corridors linking major economic corridors and other regional administrations, results in intense traffic movement across the region.

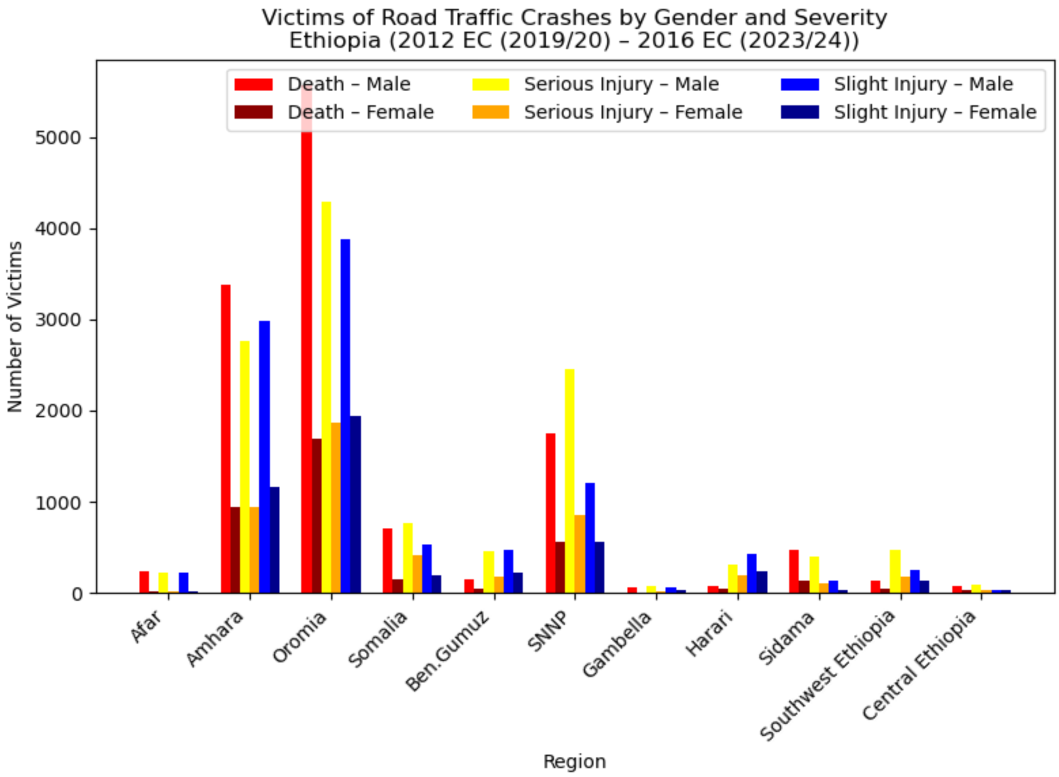

***Figure 5**: Victims of Road Traffic Crashes by Gender and Severity regions in Ethiopia (2012 EC (2019/20) – 2016 EC (2023/24)*

In all regional administrations, the incidents of crashes that lead to the loss of life and injuries are higher compared to those that lead to property damage. The statistics project a high prevalence of serious road traffic crashes. It is appropriate to state that the crashes that occur on the roads in the country are common and are associated with serious consequences in the form of loss of human life. It reveals the serious weaknesses in the conditions and policing of road safety, as well as the responses to the crashes that occur and the analysis also indicates that males are significantly more prone to involvement in road traffic crashes than females, which may be attributed to higher exposure levels, driving frequency, occupational travel patterns, and risk-taking behavior.

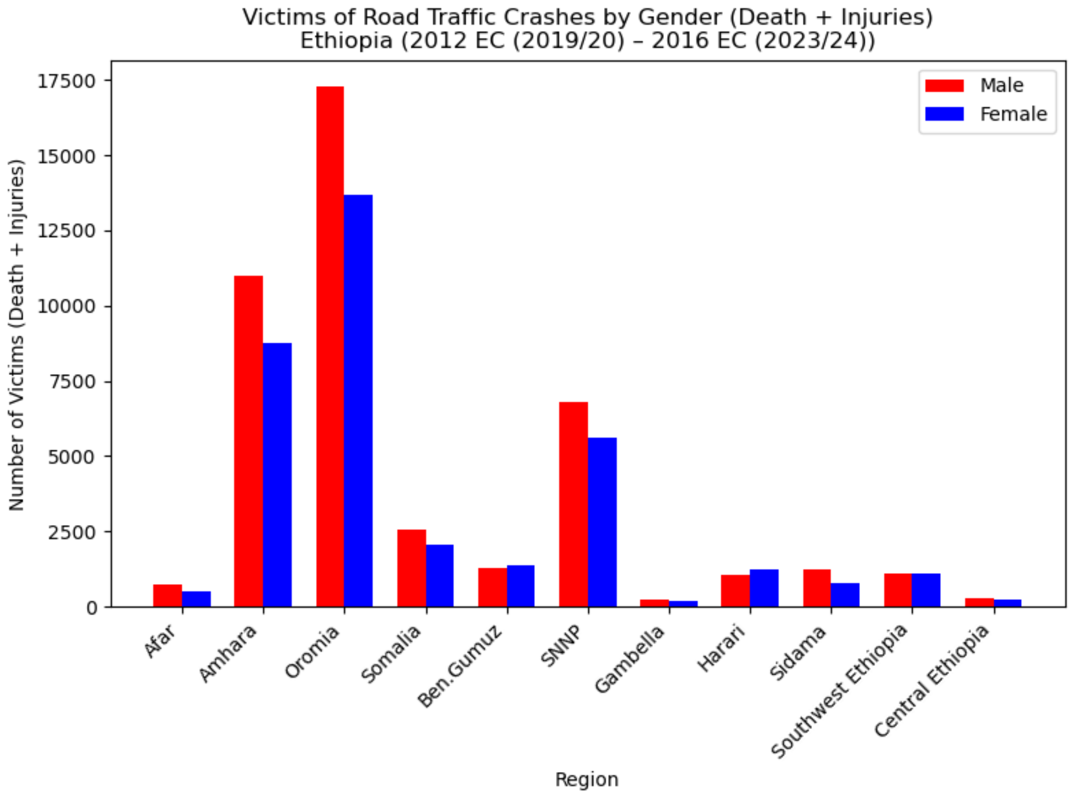

Figure 6: Victims of Road Traffic Crashes by Gender (Death + Injuries Ethiopia (2012 EC (2019/20) – 2016 EC (2023/24))

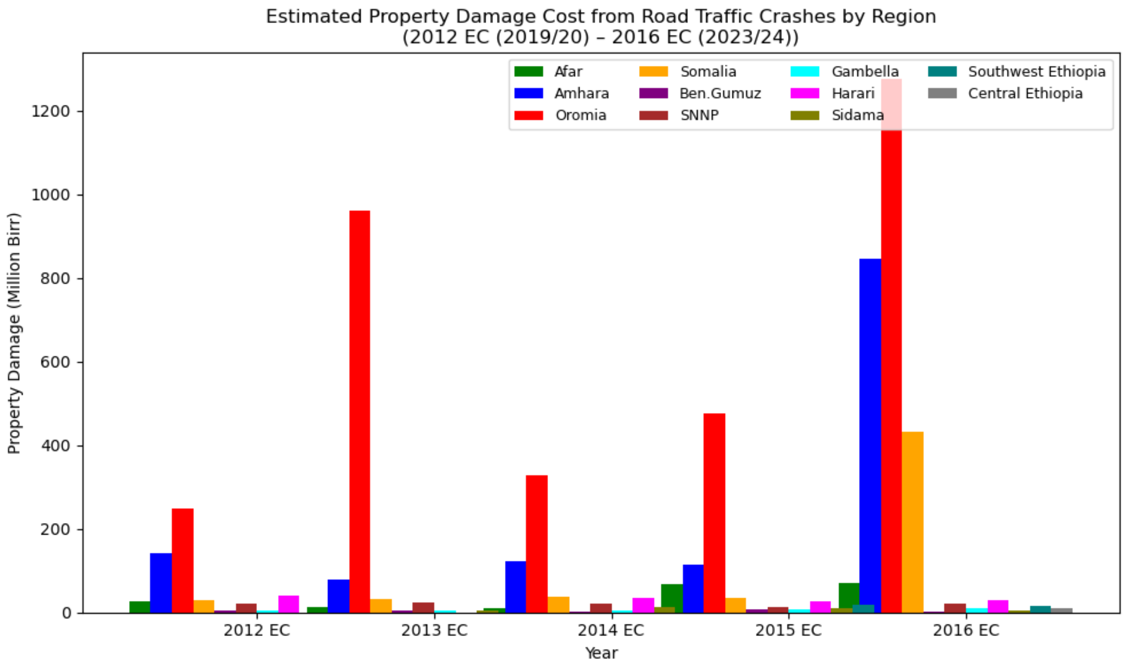

Figure 7: Estimated Property Damage Cost from Road Traffic Crashes by Region (2012 EC (2019/20) – 2016 EC (2023/24))

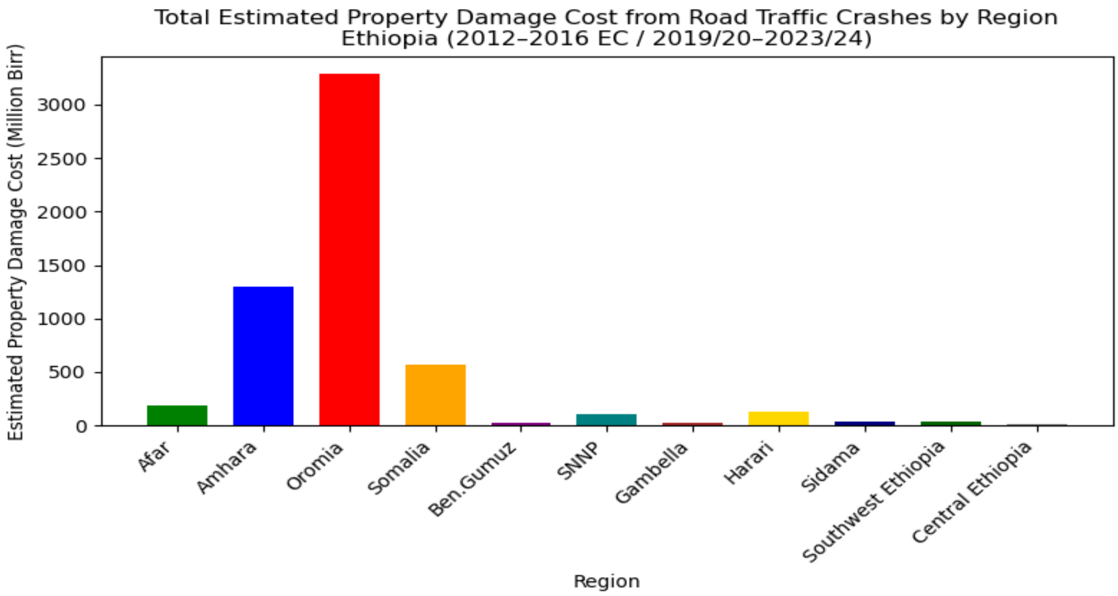

Figure 8: Total Estimated Property Damage Cost from Road Traffic Crashes by Region (2012–2016 EC / 2019/20–2023/24)

The country incurs an average annual property damage loss of approximately 2.7 billion Birr in the stated regional administrations due to road traffic crashes. This represents a substantial economic burden for a developing country; if such losses were prevented or reduced, the resources could be redirected to finance critical social investments, including the construction and improvement of medical and educational facilities

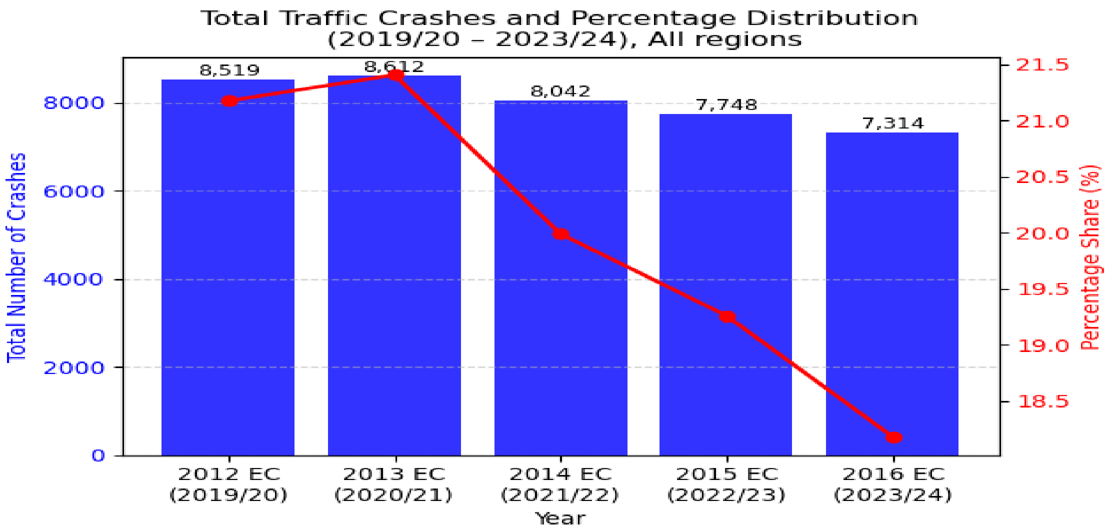

Figure 9: Total Traffic Crashes and Percentage Distribution by Year (2019/20–2023/24)

In contrast, traffic crash data obtained from the Oromia Regional Administration exhibit a pattern that differs slightly from the national traffic crash trends. The Oromia region's records indicate that total traffic crashes, fatalities, injuries, and property damage increased steadily from the 2019/20 to the 2021/22 fiscal years, reaching a peak in 2021/22. This was followed by a decline in 2022/23, after which traffic crashes increased again in the 2023/24 fiscal year. The temporal trends in traffic-related fatalities and injuries closely mirror the overall trend observed in the aggregated crash data.

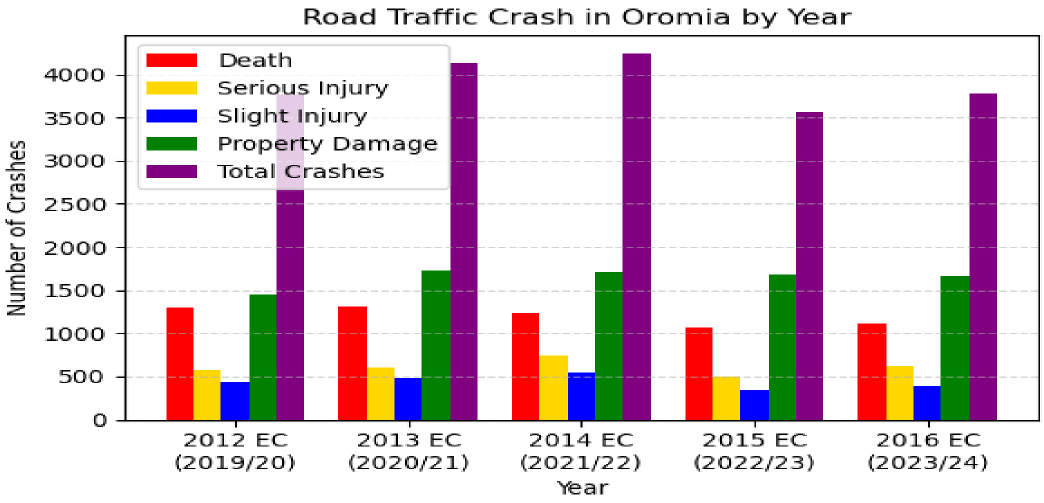

Figure 10: Road Traffic Crash in Oromia regional administration by Year (2012 EC (2019/20) -2016 EC (2023/24))

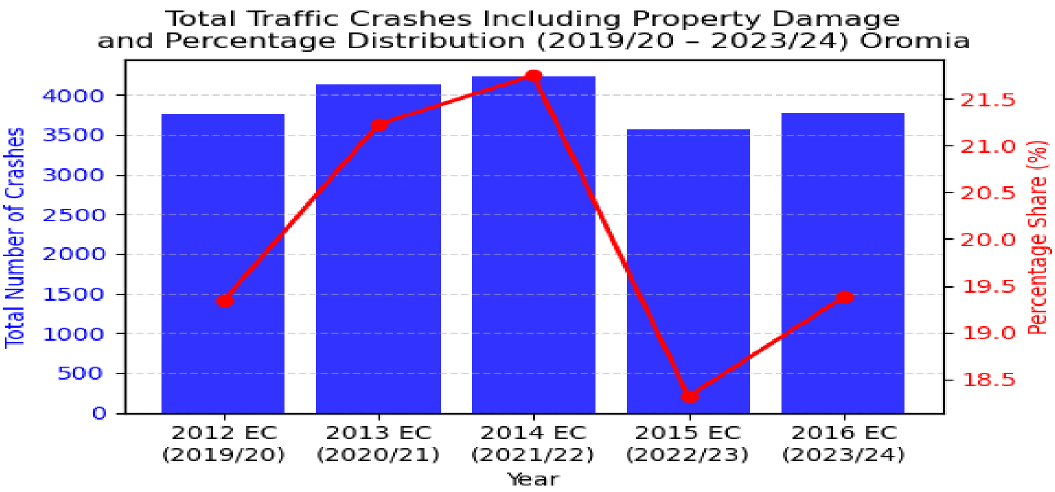

Figure 11: Total Traffic Crashes Including Property Damage and Percentage Distribution (2019/20 – 2023/24) Oromia

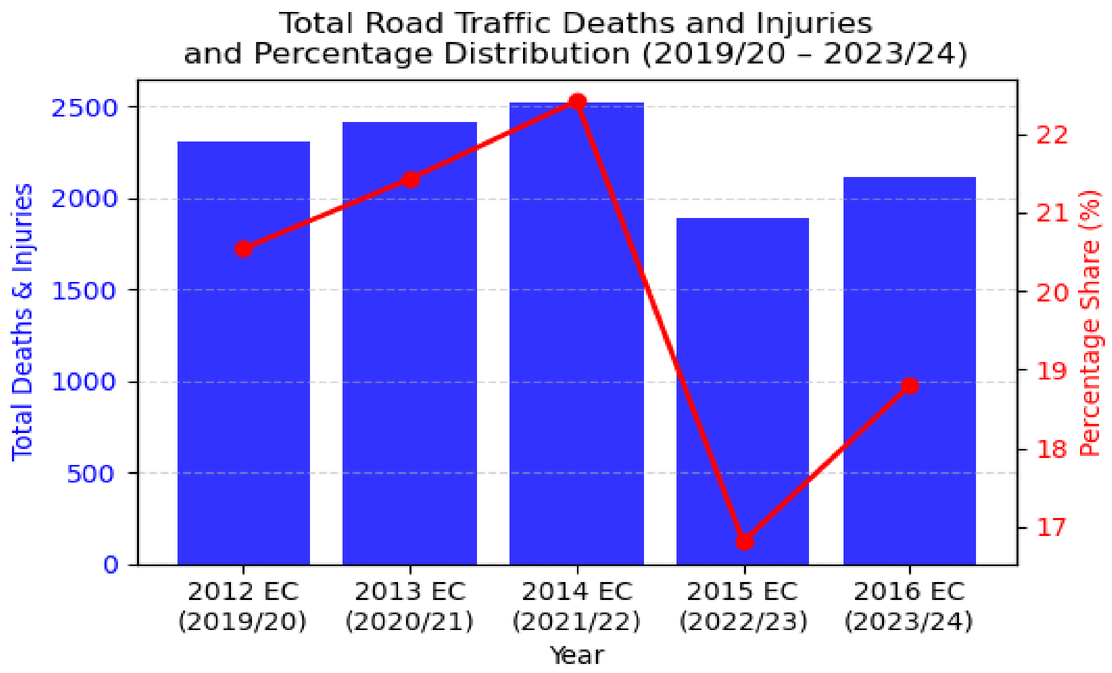

Figure 12: *Total Road Traffic Deaths and Injuries and Percentage Distribution (2019/20 – 2023/24)*

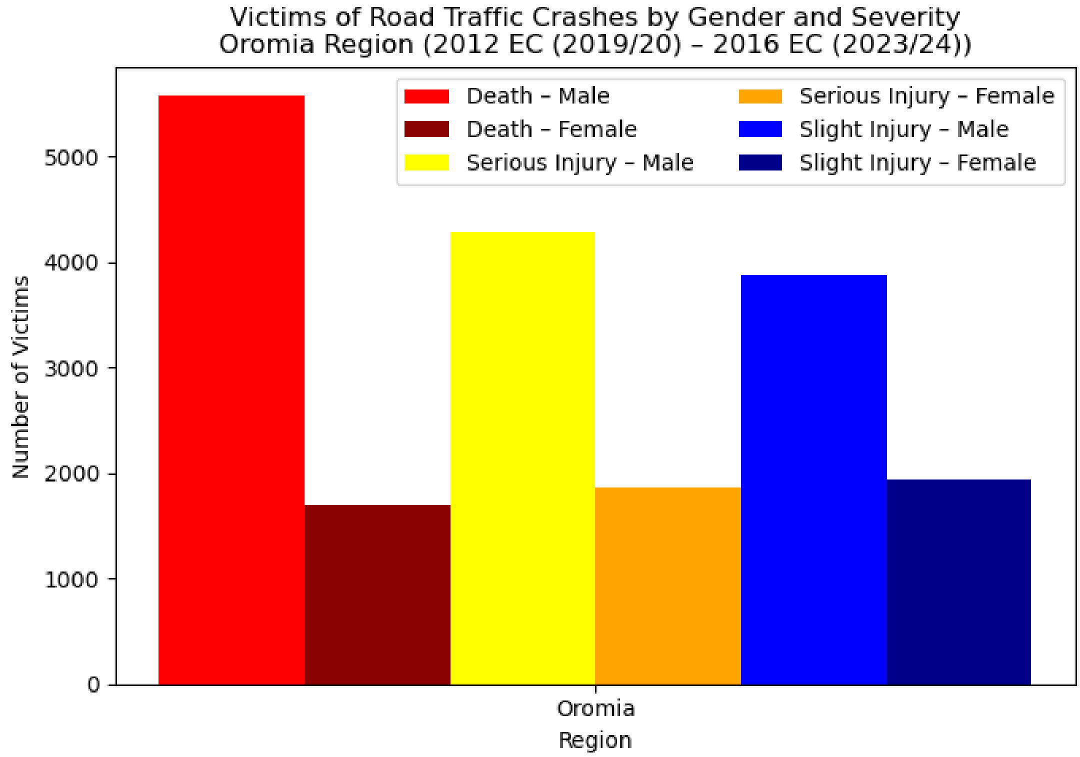

Figure 13: Victims of road traffic crashes by Gender and severity in Oromia region

Table 3: Average Annual Daily Traffic (AADT) by Vehicle Type and Truck Share across Major Road Corridors (2019–2023)

Year	Road Corridor	Passenger Car	Land Rover	Small Bus	Large Bus	Small Truck	Medium Truck	Heavy Truck	Truck Trailer	Total AADT	Total Truck AADT only	% age truck	Average % age of truck all corridors
2019	Addis - Bishoftu	2008	1965	2414	1249	2125	2148	2326	2256	16,491.00	8,855.00	53.7	51.62
	Addis - Debrebirhan	165	245	401	163	298	386	312	165	2,135.00	1,161.00	54.38	
	Addis - Comando	225	410	740	347	471	618	511	484	3,806.00	2,084.00	54.76	
	Addis - Holeta	1018	1222	1567	623	770	1576	1549	1689	10,014.00	5,584.00	55.76	
	Addis - Wolliso	1226	1393	1848	1166	1270	1649	1512	1540	11,604.00	5,971.00	51.46	
	Alemgena - Butajira	864	964	1004	904	1051	1046	1056	1065	7,954.00	4,218.00	53.03	
	Adama - Metehara	349	494	755	550	930	1168	1350	1750	7,346.00	5,198.00	70.76	
	Metehara - Awash	349	494	755	550	712	1051	1450	1862	7,223.00	5,075.00	70.26	
2020	Addis - Bishoftu	612	406	795	206	590	577	693	572	4,451.00	2,432.00	54.64	
	Addis - Debrebirhan	243	286	532	174	337	435	379	280	2,666.00	1,431.00	53.68	
	Addis - Comando	184	327	599	326	411	435	372	388	3,042.00	1,606.00	52.79	
	Addis - Holeta	719	876	1112	427	450	1087	1085	1189	6,945.00	3,811.00	54.87	
	Addis - Wolliso	1022	1151	1359	907	1056	1206	1096	965	8,762.00	4,323.00	49.34	
	Alemgena - Butajira	692	784	840	759	831	872	881	872	6,531.00	3,456.00	52.92	
	Adama - Metehara	522	632	741	667	713	991	1254	1624	7,144.00	4,582.00	64.14	
	Metehara - Awash	522	632	741	667	713	791	1369	1674	7,109.00	4,547.00	63.96	
2021	Addis - Bishoftu	2170	2128	2413	1407	2014	1987	1840	1812	15,771.00	7,653.00	48.53	
	Addis - Debrebirhan	190	311	615	186	285	218	258	207	2,270.00	968	42.64	

	Addis - Comando	185	330	590	310	399	388	380	287	2,869.00	1,454.00	50.68	
	Addis - Holeta	745	838	1970	209	398	395	324	476	5,355.00	1,593.00	29.75	
	Addis - Wolliso	677	848	1283	614	621	698	578	576	5,893.10	2,471.70	41.94	
	Alemgena - Butajira	403	482	658	425	539	521	547	414	3,989.00	2,021.00	50.66	
	Adama - Metehara	320	499	809	321	754	1236	1354	1792	7,085.00	5,136.00	72.49	
	Metehara - Awash	187	270	401	381	903	1280	1420	1653	6,495.00	5,256.00	80.92	
2022	Addis - Bishoftu	1429	1155	1580	319	672	778	540	558	7,031.00	2,548.00	36.24	
	Addis - Debrebirhan	657	1028	1554	243	425	356	285	464	5,012.00	1,530.00	30.53	
	Addis - Comando	315	468	1059	284	501	341	343	373	3,684.00	1,558.00	42.29	
	Addis - Holeta	1211	1162	3013	233	556	349	371	529	7,424.00	1,805.00	24.31	
	Addis - Wolliso	882	741	1823	406	577	444	338	261	5,472.33	1,620.00	29.6	
	Alemgena - Butajira	171	270	579	152	284	217	219	78	1,970.00	798	40.51	
	Adama - Metehara	302	500	627	199	365	652	856	1675	5,176.00	3,548.00	68.55	
	Metehara - Awash	173	319	314	130	456	752	836	1230	4,210.00	3,274.00	77.77	
2023	Addis - Bishoftu	2021	1727	2156	536	1110	1366	770	1149	10,834.94	4,395.22	40.57	
	Addis - Debrebirhan	572	922	1300	182	350	318	240	391	4,273.36	1,297.38	30.36	
	Addis - Comando	273	377	861	204	442	273	321	244	2,994.71	1,279.92	42.74	
	Addis - Holeta	969	855	2381	210	495	276	392	567	6,145.00	1,729.67	28.15	
	Addis - Wolliso	638	453	1098	259	444	357	228	201	3,677.08	1,229.33	33.43	
	Alemgena - Butajira	162	189	458	143	216	180	236	65	1,649.63	697.1	42.26	
	Adama - Metehara	185	323	407	89	652	754	837	1456	4,704.08	3,699.00	78.63	
	Metehara - Awash	40	141	139	70	356	896	1025	1546	4,211.50	3,823.00	90.78	

Source: Ethiopian Roads Administration

This study discusses the evaluation of road safety of the Adama-Awash Road segment, which is an important Federal highway and the main corridor for export and import activities in the country. The road segment crosses both the Oromia and Afar regions; however, it lies mainly within the borders of the Oromia region. Traffic crashes in the Oromia region are a serious and growing problem of public health, in addition to socio-economic problems. A research study by (Aga et al., 2021) identifies that young age (more specifically 18–30 years), limited driving experience, and risky behavior such as speeding and failure to yield are strongly associated with greater fatality in the Oromia region. Moreover poor vehicle maintenance, Older vehicles , and mechanical failures significantly linked to increase crash severity in the region (Raja et al., 2023).

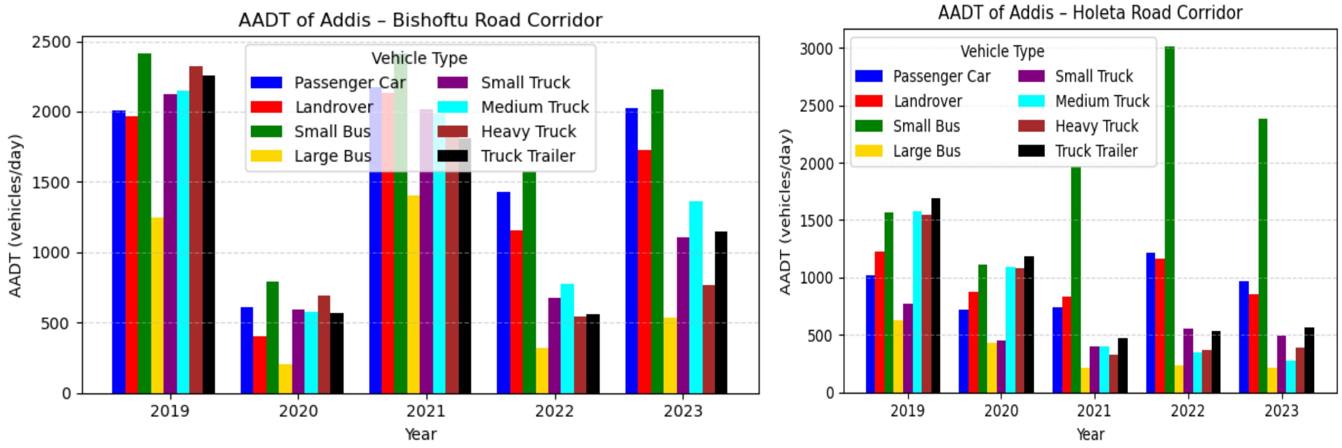

Figure 14: AADT of Addis Ababa Bishoftu and Addis Ababa Holeta Road Corridor

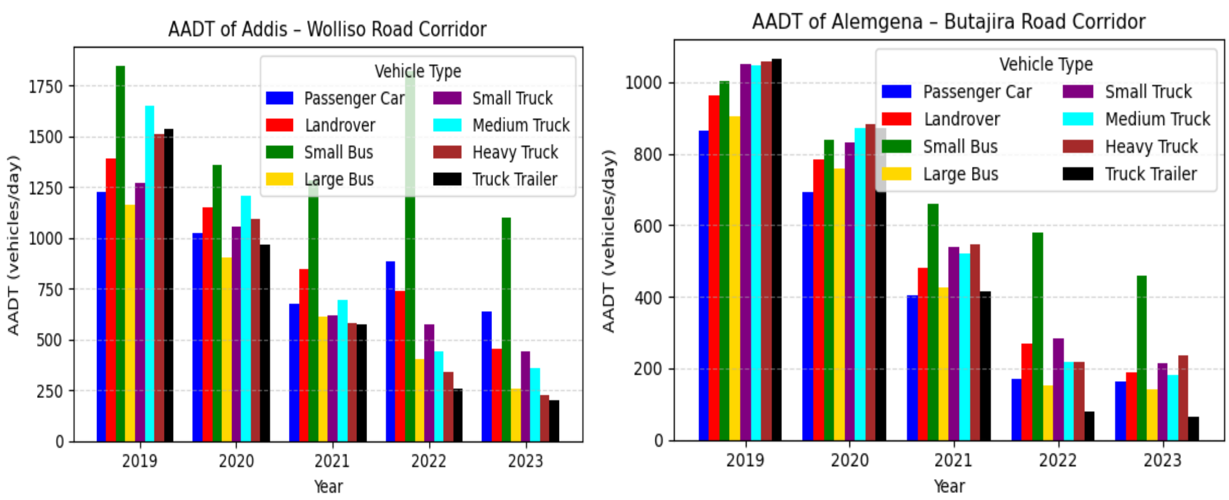

***Figure 15**: AADT of Addis Ababa Wolliso and Alemgena Butajira Road Corridor*

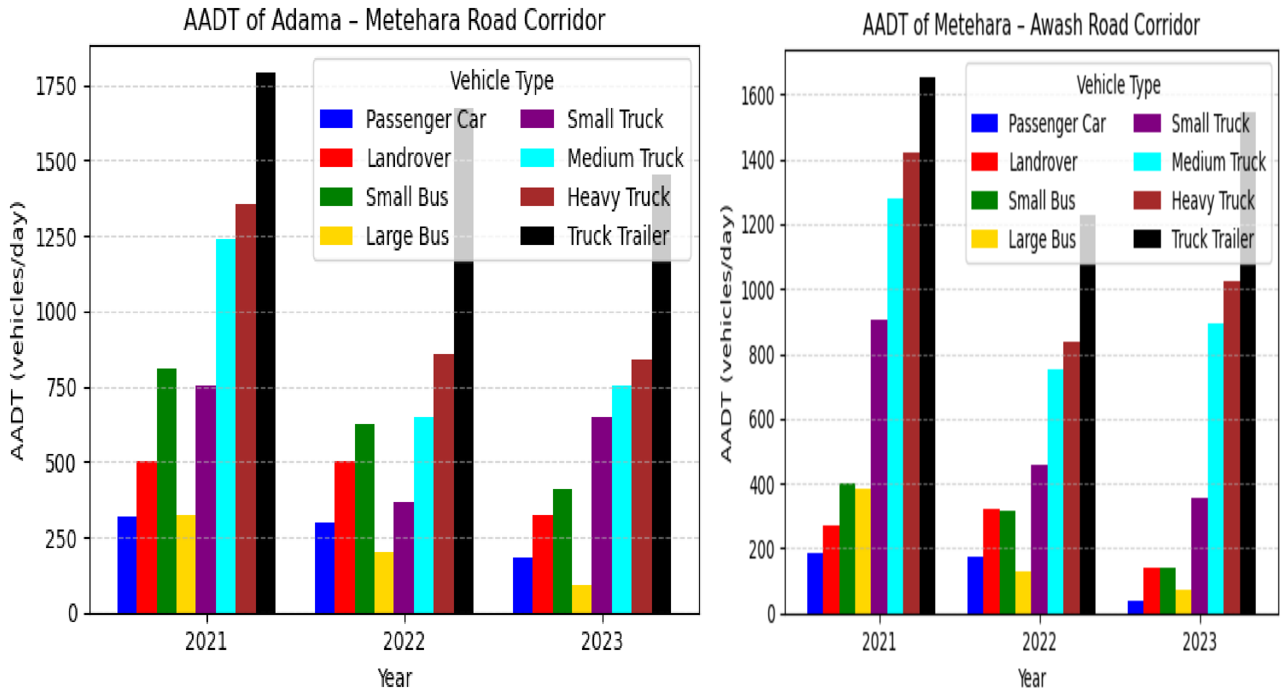

Figure 16: AADT of Adama Metehara and Metehara Awash and Road Corridor

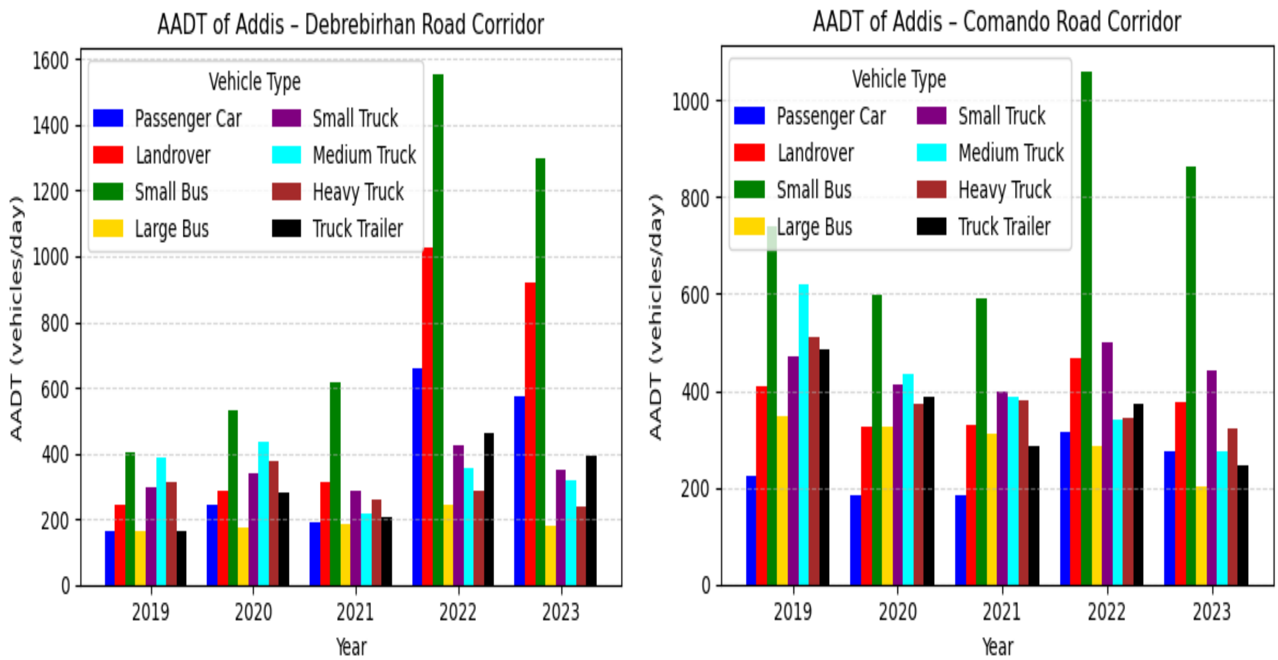

Figure 17: AADT of Addis Ababa Debrebirhan and Addis Commando Road Corridor

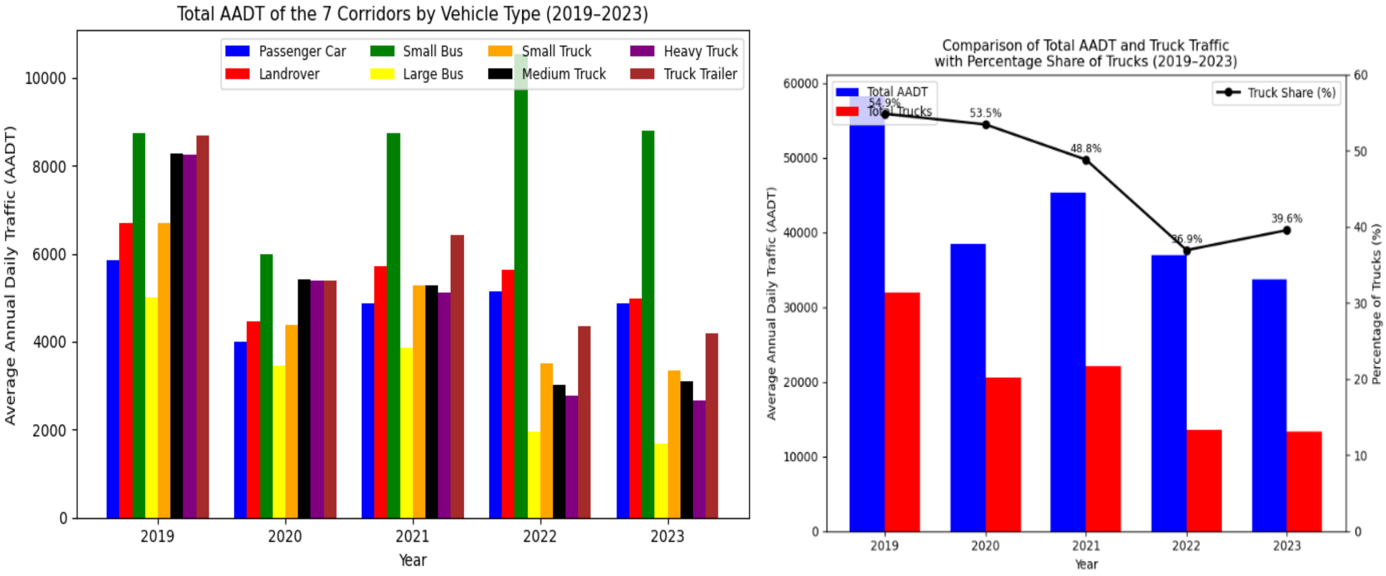

Figure 18: Total AADT of the 7 Corridors by Vehicle Type and Comparison of Truck Traffic with Its Percentage Share (2019–2023)

The Average Annual Daily Traffic (AADT) data were collected from Ethiopian Roads Administration AADT of national roads connecting Addis Ababa with different regions of the country. The primary corridors radiating from Addis Ababa include Addis- Bishoftu, Addis-Debre Birhan, Addis- Holeta, Addis-Woliso, and Alemgena-Butajira. In addition, other strategically important corridors such as Adama- Metehara, Metehara- Awash, and Addis-Comando were also considered in the analysis. All of these corridors pass through the Oromia Region, with the majority of their lengths lying within the region. This characteristic used to examine the relationship between traffic crashes and truck traffic volumes in Oromia, as they represent the region's principal freight and passenger movement routes.

As presented in Table 3 and Figure 18, the trend analysis for the period 2012 EC (2019/20) to 2016 EC (2023/24) reveals notable variations between traffic exposure and crash occurrence. Between 2012 EC and 2013 EC, total AADT decreased while the total number of crashes increased. During the same period, truck AADT also declined, whereas crash occurrences continued to rise. From 2013 EC to 2014 EC, both total AADT and truck AADT increased, accompanied by an increase in total crashes, including property-damage-only crashes as well as crashes involving deaths and injuries. In contrast, the period from 2014 EC to 2015 EC shows a simultaneous decline in total AADT, truck AADT, and total crashes (including both property damage and injury-related crashes). However, between 2015 EC and 2016 EC, total

AADT and truck AADT decreased again, while total crashes including property-damage-only crashes and crashes resulting in deaths and injuries increased.

Table 4: Trend Analysis of Traffic Crashes and AADT with Truck specific in Oromia

Year	Total crash including property damage	Total crash (Death + Injuries)	Total AADT	Only Truck AADT
2012 EC (2019/20)	3768	2315	58209	31930
2013 EC (2020/21)	4136	2415	38457	20557
2014 EC (2021/22)	4238	2527	45285	22111
2015 EC (2022/23)	3569	1895	36944	13646
2016 EC (2023/24)	3776	2119	33655	13316

Source: Road Safety and Insurance Fund Service

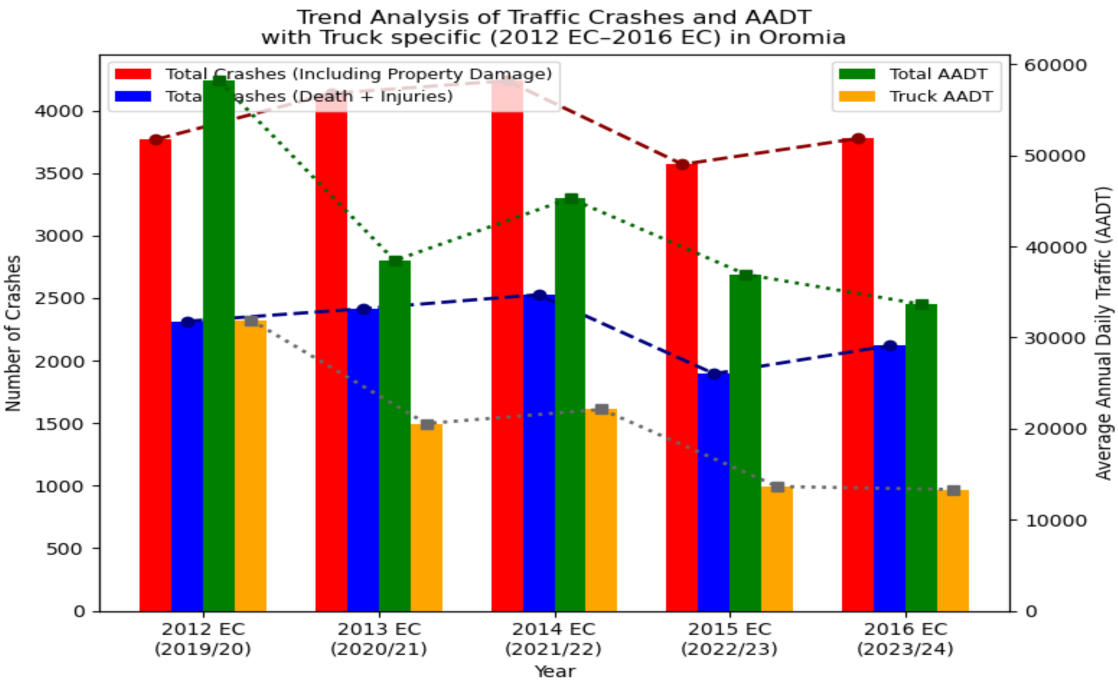

Figure 19: Trend Analysis of Traffic Crashes and AADT with Truck specific (2012 EC–2016 EC) in Oromia

The Adama- Awash road corridor is among the most vital freight transport corridor in Ethiopia connecting industrial and business centers to the port of Djibouti (FUND, 2019) and is also significant in the Country's import and export. In spite of its economic importance, the corridor has also been highly affected by frequent heavy truck crashes that result in major human, material, economic, and logistical losses. Analyzing the characteristics and underlying the root causes of the crashes are essential in the development of safety interventions and improving the corridor's overall performance.

This study aims on the safety evaluation of this freight transport corridor, and it serves as a typical example for other roads in Ethiopia. The study employs descriptive and statistical approaches to investigate the characteristics of heavy truck crashes and assess the safety performance of the corridor, using a crash data period of five years, from 2019 to 2023. The data includes details about each crash. For each factor related to the road, the study determines and summarizes the number of crashes based on severity, such as property damage, serious injuries, minor injuries, and fatalities.

Ethiopia Road Network

Ethiopia is a country of varied landscape with mountains, plateaus, and plains. The Adama-Awash Road is located in eastern Ethiopia, which is made up of mainly flat and rolling terrain. Road networks in Ethiopia are the main means of transport for people and goods and play a major role in the economic growth of the country. The efficiency and accessibility of the roads are important for the service sector and citizens as well. Through the years, Ethiopia's road network has grown tremendously. The Ethiopian Roads Administration states that Ethiopia boasts one of Africa's largest road networks, extending beyond 180,000 km, including rural and gravel roads (Meskele, 2024).

Ethiopia divides road network into two main categories:

1. **Federal Roads (National Roads):** These are the primary highways commonly known as Trunk Roads and they connect major cities of the country and are administered by the Ethiopian Roads Administration. these roads are generally wide, dual lane and receive priority in terms of maintenance rehabilitation efforts.

2. **Regional and Rural Roads:** These roads connect small towns and villages. They are usually unpaved or gravel roads fall under the jurisdiction of local regional governments. These roads may be of variable quality.

Road infrastructure in Ethiopia has been undergoing a dramatic expansion, standing at over 180,000 kilometers as of the 2022/23-year report. In terms of road network length Oromia regional state ranks highest, with Amhara, and the Southern Nations, Nationalities, and Peoples' Region (SNNPR) regional states following in descending order. However, the coverage is not balanced, favoring the Addis Ababa areas and the central part of the country, despite the target of reaching a road network of 245,000 kilometers by the year 2030 (LCA, 2024).

Table 5. Description of the Road Networks of Ethiopia

Road types	Measurement
Road Density per 1000 sq.km	145.2 km
Road Network length (in km)	180,000 km
Proportion of Federal Asphalt roads in Good Condition	24%
Paved (km)	26,550 km
Unpaved (km)	153,450 km

Source: Ethiopian Roads Administration

Being a landlocked country, Ethiopia uses the nearby Port of Djibouti as its major sea link for import and export operations, particularly for government trade. The Adama-Awash Road is an important corridor for this import-export traffic.

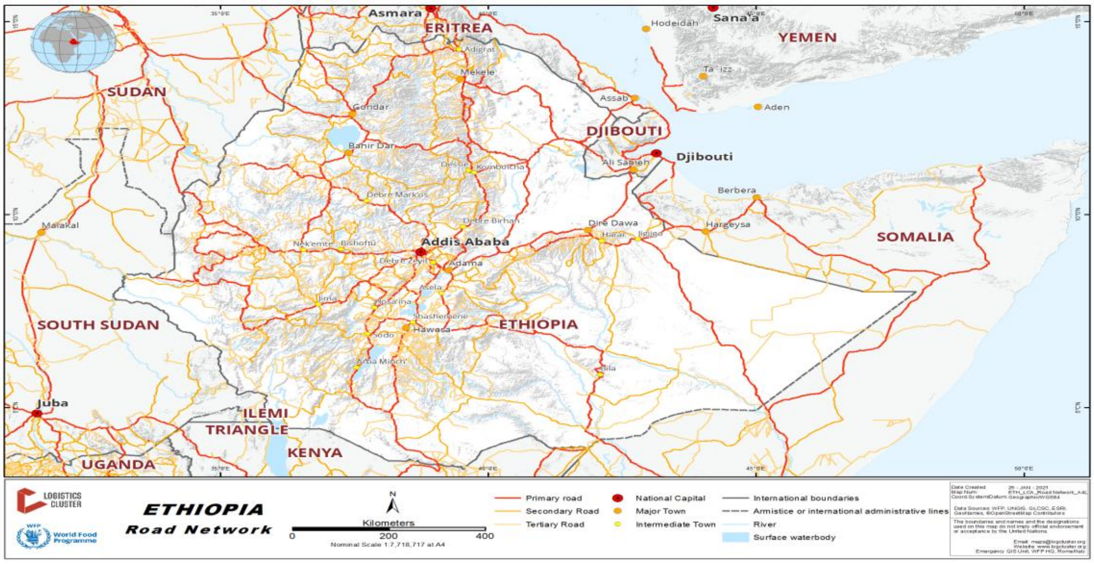

Figure 20: Ethiopian Road Networks

The Ethiopian Road network also presents various safety issues to users of the road in terms of poor road conditions, poor road signage and markings, lack of law enforcement and associated to road safety (Tadege, 2020). And the principal road traffic safety issues in the nation are as follows: drivers with poor skills, poor law enforcement, insufficient speed bumps, narrow roads and bridges, poor signs and markings on roads, inadequate attention to road safety, drivers' lack of respect for other road users, speeding, unsafe overtaking, driving closely , and failure to obey the right-hand traffic rules (Kelacha, 2021). Poor enforcement of traffic safety laws in Ethiopia is a significant cause of crashes. For instance, most drivers are caught driving while drunk, driving long hours with inadequate rest, particularly during the night, and overloading their vehicles. Goods vehicles are the most impacted. Weak enforcement of safety inspections on vehicles, such as ensuring brakes, tires, and other safety components up to standard, are also the main cause of traffic crashes (Tadege, 2020).

In order to solve these issues, the government must invest more in constructing and maintaining roads, ensure roads are in good condition, enforce traffic regulations in a very strict, and educate people more on road safety through different campaigns.

1.2. Statement of problem

Traffic crashes represent a major global public safety concern, and contributing significantly fatalities, injury, and economic disruption particularly in the developing nations (Ahmed et al., 2023). Among the different categories of vehicles involved, heavy trucks are overrepresented in serious and fatal crashes because of their size, weight, and nature of operation (Vajari et al., 2021). The safety risks of heavy truck crashes are especially happening on long-distance freight segments, where they are exacerbated by issues that include overloading, driver fatigue, vehicle mechanical deficiencies, and infrastructural deficiencies, such as inadequate road design and a lack of adequate resting areas (Gaweesh et al., 2023)

Determining the root causes of traffic crashes is often a challenging endeavor since crashes are typically the result of a combination of factors rather than a single discrete cause. It may be complex to identify the precise cause, the circumstances that exacerbated the severity of the crash, and the manner in which the contributing factors interact (Radam & Narang, 2022).

Therefore, there is a need for a deep and systematic examination to uncover these underlying factors and enable the development of effective prevention measures.

In Ethiopia, although a number of studies investigated general road safety trends, two important research gaps persist. First, although most previous studies investigated aggregated crash data (Abegaz & Gebremedhin, 2018; Bulcha, 2024), little attention has been paid to the particular features of heavy truck crashes and the determinants of their severity.

One exception is the work of (Tulu et al., 2022) who investigated heavy vehicle crashes that caused fatalities and injuries in Addis Ababa and examined the determinants of crash severity outcomes. Nevertheless, this study was conducted in an urban setting and does not cover the safety dynamics of interurban freight corridors. Second, although the Adama-Awash corridor has strategic significance in facilitating about 90% of Ethiopia's trade through Djibouti Port (FUND, 2019), no specific study has assessed crash patterns, severity determinants, or the overall safety performance of the corridor with respect to heavy trucks. The main vehicles that use the route are freight vehicles including trucks and trailer trucks.

This lack of corridor-specific and truck-centric safety studies hinders the formulation of targeted, evidence-based interventions. The corridor is not only a critical artery for national freight movement but also a cornerstone of the Ethiopian economy, supporting the flow of essential imports and exports. The safety performance of this corridor, therefore, has direct implications for the reliability and efficiency of the country's supply chains, affecting everything from the cost of goods to the competitiveness of Ethiopian trade. Poor safety performance leading to crashes and disruptions can have cascading economic consequences. To fill these gaps, this research reviews a five-year crash data from 2019 to 2023 to study the nature of heavy truck crashes on the Adama-Awash corridor. It utilizes Ordinal Logistic Regression (OLR) to determine severity determinants, including Roadway & Infrastructure related, truck related, driver and environmental related factors. Moreover, Empirical Bayes (EB) method also be used to evaluate infrastructure-related risks and determine high-risk segments. The results seek to provide an evidence-based foundation for enhancing corridor safety and guiding Ethiopia's freight transport policy to secure the economic vitality of this vital trade link.

1.3. Research question

This research aims to provide answers to the following fundamental questions about heavy truck crashes on the Adama-Awash Highway:

(1) What are the patterns and characteristics of heavy truck crashes in the corridor in relation to the crash severity, driver demographics, truck characteristics, road and environmental conditions, and temporal and spatial distributions?
(2) What are the significant contributing factors that determine the severity of heavy truck collisions?
(3) Which segments of roads along the corridor are high-risk locations regarding crash frequency and severity according to Empirical Bayes (EB)?

1.4. Objectives

1.4.1. General Objective

The general objective of this study is to investigate the characteristics of heavy truck crashes and evaluate the safety performance of the Adama–Awash freight corridor.

1.4.2. Specific objective

The specific objectives of the study are:

❖ To descriptively analyze heavy truck–related crashes in order to reveal key risk patterns and trends in severity, driver demographics, vehicle characteristics, and road environment conditions along the corridor.
❖ To investigate contributing factors to heavy truck crash severity so as to support evidence-based safety interventions and policy actions.
❖ To identify high-risk road segments in terms of crash frequency and severity along the corridor to guide targeted engineering improvements and enforcement strategies along the corridor.

1.5. Scope and significant of the study

This research is aimed at assessing the safety of a vital part of the Djibouti port corridor in Ethiopia, the 120 km Adama-Awash Trunk Road section. The objectives are to examine the descriptive characteristics of heavy truck crash, analyze crash frequency, determine contributing factors for crash severity, and determine high-risk locations along the road and it recommends interventions to minimize crashes and fatalities and consequently enhance road safety on this section and on rural roads in Ethiopia.

To achieve this goal, the study employs three main methods: a descriptive analysis of traffic crashes, ordinal logistic regression to analyze the contributing factors to the severity of crashes, and the Empirical Bayes (EB) approach to identify high-risk segments of the road in the corridor. the study uses a five-year traffic crash data (2019-2023), comprising over 651 incidents as reported by Ethiopian Federal police. Of which, 536 records (82.7%) in the reported traffic crash are heavy truck traffic crashes, revealing the major contribution of heavy trucks in crashes within the corridor. The study emphasizes on major factors such as road geometric characteristics, pavement conditions, heavy truck types, and environmental factors.

1.6. Content and outline of the Research

The research is organized into five main chapters. it includes

Chapter 1 Introduction: This section covers the background, objective and Scope of the Study and Procedures. Mainly focuses the aim and purpose of the research and importance of studying road safety on the Adama-Awash Road segment

Chapter 2: Literature Review: This section reviews different research papers related to the title of the research with particular emphasis on factors influencing traffic crashes, the methods used to measure road safety, and the effectiveness of interventions. It reviews prior studies on studies related to traffic crash severity modeling and the use of Empirical Bayes (EB) methodology for identifying high-risk roadway segments, gaps in the evaluation of road safety are the main topics reviewed.

Chapter 3: Data and Methodology: this section discussed a thorough descriptive comprehensive analysis of highway traffic crash features, including temporal attributes, heavy truck type, demographics, environmental and surface conditions, and roadway features as well as spatial distributions. These findings serve as a basis for the subsequent crash severity modeling.

Chapter 4: Results and discussion

4.2 Severity Modeling: this analyzed the severity of traffic crashes based on ordinal logistic regression (OLR) model. It investigates the association between some factors, including road conditions, types of heavy trucks, and environmental conditions, and the severity of crash to determine the most influential predictors of crash outcomes.

4.3 Safety Evaluation: In this section the Adama-Awash Road segment subjected to a safety evaluation using Empirical Bayes (EB) method and Negative Binomial Regression.

4.4 Identification of high-risk segments: It examines crash data (2019 - 2023) in light of road geometry, traffic volume, and pavement condition. and high-risk segments has identified.

Chapter 5: Conclusion and Recommendations. The summary findings of the all-previous chapters, recommendation for improving road safety and conclusions drawn from the research are presented in this chapter. Moreover, it discusses potential areas for future research activities and explores other uses of the methods applied in this study.

CHAPTER TWO

LITERATURE REVIEW

2.1. Road Traffic Safety

Road traffic crashes (RTCs) are a major public health challenges both globally and in Ethiopia, and they are causing substantial injuries and fatalities each year. In Ethiopia despite the implementation of different interventions and adoption and implementation of the Safe System Approach to enhance road safety in the country, the prevalence of RTCs in Ethiopia remains high. This highlights the urgent need for a comprehensive understanding of the magnitude of the problem, its contributing factors. Now a days in Ethiopia road traffic crashes are one of the leading causes of unintentional injuries and a national survey result shows that for every 100,000 people, 163 suffer injuries from RTAs, and 37 die, showing the severe impact these crashes have on public health (Abegaz & Gebremedhin, 2019). Some research findings show that in a specific area, like Burayu Town, 25% of RTAs result in fatalities, reflecting a serious local problem. In Mekelle city, RTAs were found to account for 23.17% of crashes among drivers (Woldu et al., 2020).

Risky driving behaviors are the most common cause of RTAs in Ethiopia. Behaviors like speeding, using mobile phones while driving, and drinking alcohol are major contributors to crashes (Hareru, Negassa, Kassa Abebe, et al., 2022; Molla, 2024; Woldu et al., 2020). Driving at night also increases the severity of injuries (Denu et al., 2021b). Vehicle-related issues, such as poor maintenance, and road-related factors, such as poor maintenance, bad road geometric designs and surface conditions, also play a crucial role in causing crashes and making them worse (Hareru, Negassa, Kassa Abebe, et al., 2022; Molla, 2024; Musa et al., 2020). Certain groups of people are more vulnerable to RTAs. Young adults, especially men, and road users like pedestrians, motorcyclists, and cyclists are at higher risk. Roughly 47.1% of RTA Casualties are between the ages of 15 and 29, and 65% of those affected by the traffic crash are male (Abegaz & Gebremedhin, 2019). Pedestrians Casualties, accounts for a significant share of the victims, underscoring the need for targeted actions to safeguard these group of people (Woldu et al., 2020).

Despite the implementation of road safety policies, the incidence of RTAs remains high, indicating the need of continuous improvement. Reviewing and strengthening safety regulations, with a particular emphasis on modifying human behavior through education and enforcement is strongly needed (Abegaz et al., 2014; Denu et al., 2021b). Enhancing emergency medical services, like improving pre-hospital care and first aid accessibility, may also reduce fatalities and speed up RTA victims recovery (Woyessa et al., 2021). Advanced data analysis techniques can also be used to identify risk factors with a high potential for severity and help to avoid serious crashes (Endalie & Abebe, 2023; Musa et al., 2020). As Road traffic crashes (RTAs) in Ethiopia indicate a serious public health emergency due to their extremely high injury fatality rate the country needs to implement a multilateral strategy that prioritizes changing the behavior of road users, addressing systemic flaws in vehicle safety laws and road infrastructure, improving traffic safety laws and their enforcement, and fortifying emergency medical response networks.

2.2. Characteristics of Heavy Truck Crashes

Heavy truck crashes represent a major safety issue across the world and in Ethiopia, particularly in freight transport corridors where unique patterns and risk factors manifest (Schindler et al., 2021; Tulu et al., 2022). These crashes are often severe as a result of a multifaceted interaction of driver behavior, vehicle factors, roadway design, environmental factors, and socioeconomic environments. Common crashes types include rear-end crashes, rollovers, and interactions with vulnerable road users such as pedestrians and cyclists. Research by (Bunn et al., 2022; Schindler et al., 2021) stated that the different crash types aggravated by poor visibility, poor road condition, adverse weather conditions, and difficult terrain. In freight corridors, roadway geometry (e.g., curves, narrow lanes, step grades), traffic volume, and built environment complexity contribute to higher crash frequency and severity (Gaweesh et al., 2023). In Ethiopia, the main contributors are high proportions of young and less-educated drivers, low safety culture within transport companies, inadequate driver training, and widespread non-owner-operated vehicles (Hagos et al., 2023; Tulu et al., 2022). Crash risk is increased during daytime and weekday periods, with speeding, wrong-side driving, and unfavorable weather conditions being key hazards (Tulu et al., 2022). Socioeconomic gradients also shape crash patterns as disadvantaged neighborhoods with proximity to logistics nodes have increased crash severity (Shin, 2024). Collectively, these results highlight the imperative of multifaceted responses including improved driver education and fatigue management, better roadway design and maintenance, traffic regulation enforcement, and implementation of cutting-edge data-driven methods for hotspot identification and focused safety treatments in freight corridors.

2.3. Impact of Pavement and Road Geometric characteristics on Road safety

2.3.1. Impact of Road geometry on Road safety

Roadway geometry plays a vital role in ensuring road safety, having a substantial influence on the frequency and severity of traffic crashes (Choudhary et al., 2024). key geometric features, such as horizontal and vertical curves, lane and shoulder widths, and sight distances, need careful consideration while designing roads. a research conducted by (Divia et al., 2016; Giri et al., 2023; Mohammed, 2013; Yin et al., 2020) on geometric characteristics of roads and safety, sharp horizontal curves and steep vertical curves are associated with high crash rates since they increase the likelihood of rollovers and skidding, especially on roads with low friction surfaces. Additionally a research by (Divia et al., 2016; Yin et al., 2020) reveled that Super elevation which is the tilting of a roadway at curves, is also another important design element in controlling vehicle dynamics. In cases where horizontal curves with small or no super elevation or have small radius, the risk of crashes is increased due to the lateral forces exerted on vehicles, which can lead to skidding or rollovers.

Furthermore, research by (Giri et al., 2023; Xie et al., 2020) indicates that narrower lanes and shoulders associated with an increased incidence of road crashes, whereas wider lanes and shoulders offer additional maneuvering space, thereby provides lateral clearance issues and improving overall road safety.

Sight distance is also a critical component of road geometry that directly affects road safety. A research by (Divia et al., 2016; Mohammed, 2013) stated that when sight distance is limited a drivers have less time to detect and react to hazardous conditions and this increases the risk of traffic crashes. An Empirical research by (Divia et al., 2016; Kelacha, 2021) also demonstrated that road segments with poor geometric design, such as an inadequate super elevation or missing , are more likely to experience to severe crashes, for example crash severity is generally greater in on roads with inadequate super elevation, especially along curves, where the combination of sharp curves and a lack of super elevation can significantly increase the risk (Jima & Sipos, 2022). Further, certain geometric feature combinations, for instance, sharp curves with narrow lanes or missing super elevation, are significantly linked with a high probability of sever crashes (Wang, 2023). Additionally, Poor intersection and curve quality, particularly with unsatisfactory signage, poor visibility and in bad pavement condition, also account for a significant portion of crash frequencies and severities. Horizontal curves, in general, have been significantly linked with traffic fatalities. Upgrading such geometric deficiencies with improved road design can remarkably enhance safety, decrease crash frequencies, and diminish crash severities, hence making road conditions safer for users (Mohammed et al., 2023).

2.3.2. Impact of pavement condition on Road safety

Pavement condition has a significant influence on road safety and crash severity. Bad pavement conditions, such as high roughness as well as rutting, often correlate with increased crash risk as well as overall level of severity, although the relationship varies with certain conditions as well as vehicle types. Bad pavement conditions, which are expressed as high International Roughness Index (IRI) as well as rut depth, correlate with increased level of crash severity, such as a high chance of fatalities (Baskara et al., 2020; Li et al., 2013; Tsubota et al., 2018). Yet, extremely bad conditions might result in more cautious driving, thus reducing crash level of severity (Li et al., 2013). Additionally, pavement roughness as well as rutting may contribute towards level of crash incidence, particularly on rural highways as well as during bad weather conditions (Chen et al., 2017; Tsubota et al., 2018). Vehicles might easily lose traction on rough pavements, therefore ending up with increased levels of crash incidence (Chen et al., 2017). Pavement conditions has also a high influence on passenger vehicles compared to commercial vehicles as poor road conditions made crashes more serious for passenger vehicles, but this was not as pronounced for commercial vehicles (Li et al., 2013; Sharif Tehrani et al., 2017). Drivers also respond to pavement conditions by changing their behavior. They slow down on very poor roads, which can reduce crash severity (Chen et al., 2017; Lee et al., 2015). Very good pavement conditions, on the other hand, may tempt drivers to speed, which could escalate crash severity (Li et al., 2013).

Maintaining good to fair pavement conditions is also important for decreasing crash rates. With proper maintenance, the decline in road safety due to the road pavement can be prevented and is advised for reducing crash risks (Li & Huang, 2014). Therefore, in conclusion pavement conditions are an important factor in road safety with a role in both the frequency and severity of crashes. Poor conditions tend to raise crash risks whereas very good conditions may occasionally result in more dangerous driving. Proper pavement maintenance is important for the improvement of road safety and lowering crash rates.

2.4. Driver and Environmental related safety factors

Traffic crash is a complex issue in transportation and it influenced by a combination of vehicle-related, driver-related, and environmental factors. Environmental factors, including climatic conditions such as extreme temperature, for and heavy rain plays a significant role in increasing the likelihood of road traffic crashes. In Pakistan, for example, weather-related factors such as fog and rain have been directly associated to higher crash rates (Hammad et al., 2019). In addition, poor road infrastructure, a lack of traffic signals, and high-risk crash zones further increase traffic injuries and fatalities (Klinjun et al., 2021).

Driver behavior as well as driver characteristics are central in establishing traffic safety. Age, alcohol consumption, as well as driving during adverse weather conditions, are significant risk factors. Younger motorists, particularly under the age of 25 years, are more prone to crashes, especially with a combination of alcohol consumption as well as adverse weather conditions (Casado-Sanz et al., 2020). Driver fatigue, over speeding, as well as a disregard for wearing seatbelts, are common human errors accountable for crashes (Klinjun et al., 2021).

Traffic crash needs to be managed with a comprehensive intervention considering the interplay between human, vehicle, as well as environmental factors. Matrixes like Haddon matrix are helpful for identifying risk factors both before and after crash occurrence and provide a clear view of causation of traffic crashes (Klinjun et al., 2021). Special traffic regulations and safety education programs for certain groups of motorists as well as certain categories of vehicles can contribute a lot towards reducing crash rates as well as deaths (Xie et al., 2020).

2.5. Freight Corridor Safety

Freight corridors are critical for transport of goods but they are also prone to traffic safety problems, notably with increasing flow of heavy truck vehicles. Numerous studies outlined a different factor that influence freight vehicle crash frequency and severity, including roadway geometric characteristics, vehicle characteristics, driver behavior, and environmental factors (Taylor et al., 2018; Wang et al., 2022). A research by (Yang et al., 2021) outlined that crashes involving large vehicles and crashes occurring at midblock segments or rural highways tend to exhibit more serious outcomes. The environmental condition, land use, and road network features impacts crash likelihood as well as severity to a significant extent, with a high level of urbanization having more significant issues owing to increased freight concentration. A United States study highlighted that vulnerable road users, including pedestrians and bicyclists, faced much higher risks in heavy truck-involved crashes, often involving serious or fatal injuries (McDonald et al., 2019; Wang et al., 2022). Research by (Dadashova et al., 2020; Gaweesh et al., 2023) revealed in freight corridor horizontal and vertical curvature, steep grades, and inadequate super elevation increase severity, especially on mountainous or interurban freeways. Another study by (Sadeghi & Goli, 2024) reported that low friction, rutting during rain or night conditions, and surface roughness significantly increase crash risk, with the effects varying depending on road class and vehicle speed. In order to solve such problems, a research by (Sharma et al., 2023) different safety measures have been proposed, including providing heavy truck lanes, heavy vehicle restrictions, heavy truck dedicated advanced traffic signal detection, as well as education programs aimed at a selected concern issues and identified groups, which was seen to result in safety benefits with respect to a reduction in crashes as well as improvements in corridor performance. Additionally, a study by (Taylor et al., 2018) stated that with such freight traffic volumes expected to continue increasing, it’s important that a comprehensive safety approach towards facilitating both a safe as well as efficient freight transport system, including measures related to road infrastructure, regulation, as well as traffic management technologies, should be adopted.

2.6. Vehicle, Driver and Environmental related safety factors in Ethiopia

Road traffic crashes in Ethiopia are a major public health issue, and multiple factors influence their frequency and severity. These can be classified into vehicle-related, driver-related, and environmental factors. Identification of these determinants is important for instituting prevention measures. Driver behavior is a leading cause of road traffic crashes in Ethiopia. Dangerous acts such as speeding, drinking and driving, and use of mobile phones while driving highly elevate the risk of crashes (Abegaz et al., 2014; Hareru, Negassa, Kassa Abebe, et al., 2022; Molla, 2024). Drivers with limited driving experience and those with lower education levels exhibit increased vulnerability to being involved in crashes, pointing to the need for improved driver education and training (Tadege, 2020; Zenu et al., 2023).

Moreover, weekend driving and during particular seasons, for instance, summer, have been linked to increased crash rates (Tadege, 2020). Vehicle condition and maintenance also have a key role in road safety. Mechanical defects and vehicle age are major causes of crashes (Hareru, Negassa, Kassa Abebe, et al., 2022; Molla, 2024; Zenu et al., 2023). Regular vehicle maintenance and thorough safety inspections plays a crucial role in reducing these risks (Hareru, Negassa, Kassa Abebe, et al., 2022; Zenu et al., 2023). In addition combination of factors, such as weather and type of road, also affect the occurrence and severity of road traffic crashes (Abegaz et al., 2014; Endalew et al., 2024). Non-asphalt road types and unfavorable weather conditions, like rain and wind, have been associated with increased crash rates (Abegaz et al., 2014; Molla, 2024).

To decrease the incidence of road traffic crashes, several strategies have been suggested, including the enforcement of stricter punishment for traffic violations, increasing driver education programs, and increasing public awareness of the importance of road safety (Akbari et al., 2024). Additionally, the development of road infrastructure and ensuring periodic vehicle maintenance are key actions for decreasing the probability of crashes.

2.7. Improvement measures to minimize road safety problems

Road traffic safety enhancement demands an integrated legal, technical, educational, and infrastructural approach (Guketlev et al., 2019). Strict enforcement of traffic regulations, including speed limits and drink-driving penalties, is essential including adopting international best practices, like from Poland, can improve vehicle safety on the roads (Goniewicz et al., 2016; Mohan et al., 2020). Regular Road safety audits and inspection, especially on rural roads and highways, can detect and remedy potential safety problems prior to their involvement in crashes(Ai et al., 2024). Implementing Low-cost traffic engineering treatments such as speed humps, raised intersections, and better road markings can effectively decrease crashes, particularly in urban areas (Batishcheva & Ganichev, 2018; Yannis et al., 2014). Further, Intelligent Transport Systems (ITS) such as Intelligent Speed Adaptation and urban traffic control systems can manage traffic flow, make driving tasks simpler, and decrease environmental complexity, consequently decreasing crash risks (Pugachev et al., 2020). Educational campaigns aimed at raising awareness and improving the behavior of drivers are important, especially when supported by widespread enforcement activities (Mohan et al., 2020). Programs aimed at enhancing the decision-making skills of drivers and pedestrians can help lower the incidence of crashes due to human factors (Batishcheva & Ganichev, 2018). Tailoring traffic safety measures to suit local conditions, particularly among vulnerable groups like children and older adults, is vital in order to maximize safety outcomes. Setting specific localized targets and implementing targeted interventions at the local community level further strengthens road safety initiatives (Čabarkapa & Avramović, 2017).

Thus, an integrated strategy that integrates legal enforcement, technological advancements, education, and community-tailored interventions is needed to reduce road traffic safety issues (Safarpour et al., 2020). These measures need to be tailored to the local situation and made subject to constant review of effectiveness in order to secure the safety of all road users.

2.8. Crash severity modeling

Crash severity indicates the level of damage caused by vehicular crashes. There are different classifications of crash severity in use in various countries. In Ethiopia, the documentation and reporting of crashes use four different categories to indicate crash severity: Fatal, Serious Injury, Slight Injury, and Property Damage Only (Tola et al., 2022).

Variables in crash severity modeling categorized in to two namely independent and dependent. The researcher controls independent factors in order to look at how they affect the dependent variable. Usually the outcomes under study, dependent variables are those that are impacted by changes in the independent variable. Independent variables are also manipulated or controlled by researchers to observe their effects on dependent variables, which are the outcomes or responses being measured. Accurate description and control of independent variables, also known as treatment, intervention, predictor, or risk factors, are crucial for ensuring the reliability and validity of research findings (Andrade, 2021; Flannelly et al., 2020; Han et al., 2023).

Traffic crash severity modeling is a critical research field aimed at determining the factors that influence the severity of road crashes. Several modeling approaches are utilized in the analysis of crash severity. These include Ordinal Logistic Regression, which is applicable where severity measures are ordered; Multinomial Logistic Regression, which is applied in the case of unordered severity categories; Decision Tree Techniques, which offer an interpretable method of classifying crashes by contributing factors; and Artificial Neural Networks, which are capable of capturing intricate, non-linear relationships in crash data for better predictive power. Some other models such as Multi nominal Logit and Negative Binomial models within the Bayesian estimation framework are utilized to investigates the effects of risk factors on frequency and severity of large truck–involved crashes (I. Asare & A. Mensah, 2020; Dong et al., 2017; Liu et al., 2023)

2.8.1. Multinomial Logistic Regression Model

Multinomial logistic regression (MLR) is a statistical modeling technique used to predict the outcomes of a categorical dependent variable that has more than two categories. Unlike binary logistic regression, which deals with dichotomous results, MLR can handle multiple categories with no natural order. The technique extends logistic regression to allow comparisons between each category of an unordered response variable compared to a reference category(Wen et al., 2023).

For a response variable having j categories, the model is composed of j−1 logit equations that are estimated simultaneously. The method of estimation is based on maximum likelihood estimation, which is most appropriate for dependent variables having multiple unordered categories. The method is highly applicable in areas like nursing research, whereby it allows the modeling of intricate categorical data without the need to collapse the categories into binary outcomes (AJEEL et al., 2023).

MLR is used extensively across many fields, such as health, Engineering, social, behavioral, and educational research, and thus proves to be useful when analyzing data with nominal or ordinal response variables with more than two categories. However, MLR models are prone to challenges such as over fitting, especially in small to medium-sized data sets. to address this MLR is usually recommended in order to improve calibration and predictive capability, especially when the sample size is limited or when outcome categories are imbalanced. Another issue is robustness to outliers since standard MLR models can experience degradation in performance when they are present. In order to fix this problem, rank minimization and robust principal component analysis-based robust MLR methods have been proposed, which guarantee improved classification accuracy even under noisy data (Sainani, 2021; Sofro et al., 2023)

2.8.2. Ordinal logistic regression

Ordinal logistic regression (OLR) represents a widely utilized statistical technique as it proficiently captures the sequential characteristics inherent in the severity outcomes of crashes.

Several studies reveal that ordinal logistic regression models are useful in identifying key variables influencing the severity of road crashes, such as road conditions, and the geographical location of the crash (urban and rural), driver behavior, vehicle characteristics, and environmental conditions. In addition, the utility and applicability of the models have differences based on specific contextual factors and data types(I. O. Asare & A. C. Mensah, 2020). Speeding and high-speed violations are fundamental contributors to more severe crashes(I. O. Asare & A. C. Mensah, 2020; Russo & Savolainen, 2018). Driver behavior, including distractions or sleepiness while driving and the failure to use seat belts, also plays an important role in shaping outcomes, with older drivers being especially vulnerable due to aging factors and distraction (Alrumaidhi & Rakha, 2022; Gooch et al., 2024). Furthermore, the time of day, seasonal, and environmental and temporal factors like weather, road surface, and lighting are also affect the severity of the crash (Darwish & Darwish, 2023; Kronprasert et al., 2021; Yuan et al., 2020).

Ordinal logistic regression (OLR) is a valuable technique for identifying key predictors of crash severity, particularly when data sets are limited or does not sufficiently represent population attributes(I. O. Asare & A. C. Mensah, 2020; Darwish & Darwish, 2023). Multilevel ordinal logistic regression (M-OLR) enhances model fit through the accommodation of spatial heterogeneity, thereby being useful in studies covering diverse geographical areas (Alrumaidhi & Rakha, 2022, 2024). However, model complexity is a major hindrance, as researchers are often confronted with having to choose between ordinal models and non-ordered counterparts like multinomial logistic regression. The partial proportional odds model provides a balanced approach by allowing some predictors to have varying magnitudes of effect across different severity levels.

In this study, the Ordinal Logistic Regression model has been used because the dependent variables (crash consequences: fatality, severe injury, minor injury, and property damage) are in an ordered or ranked manner. This feature makes OLR a suitable method of analysis to examine crash severity, as it identifies the natural ranking of the outcome categories and allows for a meaningful interpretation of the effects of the predictors on crash severity.

A special case of the generalized linear model that generalizes ordinary linear regression by allowing the linear model to be related to a response variable that follows the exponential family via an appropriate link function.

When the response variable is binomially distributed with parameter P_i, the logit function is used as the link function. The logistic regression establishes the relationship between the response variable y= (y_1,..,y_n) given P= (P1,…,Pn) and a set of k predictors, X = (X_1,…,X_k).

In this study the five-year crash data was statistically analyzed using ordered logistic regression. The log-odds of cumulative probability are used in this method. This is frequently obtained by supposing that a latent response variable γ has a linear relationship (I. Asare & A. Mensah, 2020).

$$\gamma_i = \alpha + x_i'\beta + \varepsilon_i = \alpha + \eta_i + \varepsilon_i \qquad \textit{(Equation 1)}$$

Where x_i is the i^{th} row of the model matrix, ß is a vector of regression coefficients, and α is an intercept parameter (which proves redundant). Although the latent response cannot be observed directly, a binned version of it, y, with m levels is available as follows.

$$y_i = \begin{cases} 1\ for < \alpha_i \\ 2\ for\ \alpha_i < \gamma_i \le \alpha_2 \\ . \\ . \\ . \\ m-1\ for\ \alpha_{m-2} < \gamma_i \le a_{m-1} \\ m\ for\ a_{m-1} < \gamma_i \end{cases} \qquad \textit{(Equation 2)}$$

Where the thresholds given $\alpha_1 < \alpha_2$ ------- α_{m-1} are parameters to be estimated from the data along with the regression coefficients. The cumulative distribution function of the observed response is given as follows.

$$p_r(y_i \le j) = p_r(\gamma_i \le \alpha_i)$$

$$= P_r(\alpha + \eta_i + \varepsilon_i \le \alpha_j)$$

$$= p_r(\varepsilon_i \le \alpha_j - \alpha - \eta_j) \qquad \textit{(Equation 3)}$$

For j= 1, 2… m-1. Assuming that the errors ε_i are normally distributed produces an Ordered Probit Model; assuming that the errors are logistically distributed, with distribution function:

$$\Lambda(\varepsilon_i) = \frac{1}{1+e^{-\varepsilon_i}} \qquad \textit{(Equation 4)}$$

Produces an ordered logit model:

$$logit[p_r(y_i > j)] = log_e \frac{p_r(y_i > i)}{p_r(y_i \leq j)}$$

$$= -\alpha_j + x'\beta \quad 1; 2; \ldots m\text{-}1 \qquad \textit{(Equation 5)}$$

Equation 5 fixes the origin of the latent response by setting the intercept α to 0 to identify the model. This approach defines what is known as the proportional-odds model. In this model, different expression cumulative log-odds, logit [P_r (y_i > j)] and logit [Pr (y_i >j')], differ by the constant $\alpha_{j'}$- α_j, and therefore the odds remain proportional regardless of the value of x'_i.

Every level of y, with the exception of the final one, has a distinct intercept that is equal to the threshold's negative. The coefficient vector ß, however, is constant at all levels. A fundamental principle of the ordered logistic regression model is the parallel curves assumption, which asserts that the relationship between predictors and the outcome remains constant across different threshold levels.

From the five years of crash data, 21 independent variables that are driver-related, vehicle, road geometry and pavement condition, environmental condition predictors, were identified. To choose which variables to include in the model, the chi-square test (X^2) of independence was used. This test was conducted to test the independence between crash outcomes and the independent variables, and the result found that 12 variables were identified as significant predictors with a p-value < 0.05.

The next step was a Brant test of the parallel regression assumption performed in order to check if the collected five years of crash data satisfies the proportional odds assumption of the OLR model. By testing if the assumption holds (p>0.05), then it is safe to use it in the OLR model. After the Brant test, a correlation and collinearity test has been performed using a variance inflation factor (VIF) and tolerance to check if there is a correlation between the 12 significant predictors and the result reveals that there is no correlation among the 12 variables. Finally, an OLR model was applied to analyze the crash severity.

2.8.3. Random parameter logit regression

Random parameter logit regression models have also proved to be an efficient tool in the analysis of crash severity, largely due to their ability to represent unobserved heterogeneity in crash data. Unlike fixed-parameter models, where the heterogeneity in the impact of explanatory variables is assumed to be homogeneous, random parameter models allow these impacts to be different for each observation. Unlike other logit model which states each explanatory variable has the same effect across all observations the random parameter logit model allows some coefficients to vary across observations like, across crashes, vehicle types, or locations (Gong et al., 2021; Ye et al., 2021; Yu et al., 2020). So, this is the advantages offered by the random parameter logit regression models that represent heterogeneity, thereby providing more accurate results for different types of road crashes involving single vehicles, two vehicles, and vulnerable road users and the model identifies key determinants of crash severity, these are driver and vehicle characteristics such as age, gender, dangerous driving behaviors (e.g., speeding, distraction), vehicle type, driver condition (e.g., fatigue or drowsiness) which commonly have random effects. Environmental and roadway factors also significantly contribute, with weather conditions, lighting, road surface condition, road geometry, and time of day typically impacting crash severity in manners that differ across crashes (Azimi et al., 2019; Cai & Wei, 2023; Okafor et al., 2023; Yu & Long, 2021).

Regarding model performance, random parameter logit models demonstrate high predictive accuracy, especially when marginal effects are computed using Monte Carlo simulation techniques (Hou et al., 2021). These advanced approaches not only improve our understanding of crash severity dynamics but also help the establishment of more effective policy and mitigation measures (Hou et al., 2022; Moomen et al., 2023; Sun et al., 2023).

2.9. Empirical Bayes Method

Road safety evaluation and analysis on a segment basis commonly rely on statistical models for crash risk prediction and identification of dangerous locations, where the Empirical Bayes (EB) method and Negative Binomial (NB) regression have become the cornerstones in road safety research (Khattak et al., 2024; Persaud et al., 2010). The EB method enables more accurate delineation of crash risk estimates by incorporating crash count observations with predictions from models, thereby removing regression to mean bias and improving the accuracy of predicted crash values (Khattak et al., 2024; Persaud et al., 2010). At the same time, the NB regression method remains the preferred choice for crash data modeling, thanks to its capability to address over dispersion in crash frequencies, where the variance is higher than the mean (Khattak et al., 2024; Persaud et al., 2010).

In a bid to improve these models' performance capabilities and overcome complications from real-life crash date, various modified versions from the NB models have been proposed in recent years for more comprehensive treatment of complications from excess zero values, unobserved heterogeneity, and variability (Khattak et al., 2024; Meng et al., 2020; Zou et al., 2018). Additionally, geographically weighted NB regression models, combined with simulation-based Empirical Bayes approaches, make efforts to incorporate location-specific factors into the models for improved fits and more accurate identification thereof (Bakhshi et al., 2022; Tahir et al., 2021). Comparative analyses study conducted by (Khattak et al., 2024) reveal that while the standard NB+EB approach offers simplicity and effectively addresses regression-to-the-mean, it has also overlook spatial and heterogeneous effects while a study by (Albrecht & Hasan, 2025; Wood & Donnell, 2017) highlights that mixed-effects NB models and geographically weighted regressions provide robust estimations under complex conditions but demand more sophisticated data and analytical procedures. Key studies demonstrate the usefulness of such models for hotspot detection, spatial analysis, and bias reduction in safety analysis therefore integrating EB with NB regression establishes a coherent framework for segment-level road safety analysis and enhances accuracy, robustness, and practicality for transportation safety management and decision-making.

The crash rate examination covers the Adama-Awash Road section, a 120-kilometer countryside road that goes via many towns, settlements, and villages. In an effort to improve the accuracy of the review, the route was divided into four segments, as discussed in the introduction part of this study. Using AADT and five years of crash data (2019-2023), crash rates were computed. The investigation includes all known kinds of reported crashes, that is fatal crashes, serious injury crashes, slight/minor injury crashes, and property damage only (PDO)The next step is Safety Performance Function (SPF)

For rural two-way highway, Negative Binomial (NB) regression can be used to predict expected crashes (E(Y) based on AADT. The general formula for the Negative binomial can be given by (Dissanayake & Ratnayake, 2006);

$$log(E(Y)) = \beta_0 + \beta_1 log(AADT_i) + \beta_2 x_{i1} + \beta_2 x_{i1} + \cdots + \mathcal{E}_i \qquad \textit{(Equation 6)}$$

Where, E(Y) is the expected count (the dependent variable, Observed, Y), β_0 is the intercept (constant term), β_1, β_2…, are regression coefficients for each predictor or independent variables.

Compute Empirical Bayes Weight (w) is calculated in the next step using;

$$w = \frac{E(Y)}{E(Y)+\frac{1}{\phi}} \qquad \textit{(Equation 7)}$$

Where, W is Empirical Bayes Weight (w), E(Y) is Predicted Crashes, and Φ is Over Dispersion Parameter, which calculated by;

$$\emptyset = \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 - Y_i}{\sum_{i=1}^{n}\hat{Y}_i^2} \qquad \textit{(Equation 8)}$$

Where, Y_i is observed crash count for segment i, $\hat{Y}_i$ is predicted crash count for segment i, n = number of observations and p is number of model parameters. Lastly to identify hotspot segments using the EB method, it starts with calculating the Empirical Bayes (EB) Estimate. The Empirical Bayes (EB) Estimate is the adjusted or shrinkage estimate of yearly for each road segment. This involves the observed crashes (Y) and the calculated forecasted crashes (E(Y)), and scaled by the empirical Bayes weight (w). Especially in an event of over-dispersion, this step ensures the improvement of the estimates by decreasing the highly observed crashes to the forecasted estimates. The values of the estimates use the following equation.

$$EB\ Estimate = w * Y + (1 - w) * E(Y) \qquad \textit{(Equation 9)}$$

This is applied for a safety evaluation of the Adama Awash rural road segment, a 120-kilometer road serving as a main import-export corridor in the nation. The road's kilometer reading begins at Adama (0 km) and extends to Awash (120 km). For the sake of higher analytical precision, the road segment was split into four segments: 0-20 km, 20-52 km, 52-80 km, and 80-120 km by applying the Empirical Bayes (EB) method.

A Five-year crash data (2019-2023) including Annual Average Daily Traffic (AADT), geometric characteristics (average curvature, lane width, slope, sight distance), and pavement properties (pavement age, percent of cracking, International Roughness Index (IRI)) were considered for the analysis. A Negative Binomial (NB) regression model was applied for the prediction of crash occurrences for each and every segment of the roadway, identifying significant associations between crash frequency and coefficients such as AADT, pavement age, IRI, sight distance, and percent of cracking.

2.10. Gaps in the evaluation of Road safety

The evaluation of road traffic safety has different critical gaps that need to be addressed to improve global road safety outcomes, particularly in sub-Saharan countries like Ethiopia, where traffic crashes are the main reason for death. These gaps are related to inadequate infrastructure, insufficient policy implementation , data inconsistency, , and a lack of proper interventions (Neki et al., 2023).

Despite developing countries experience high rate of road traffic crashes, there is a gap in road safety evaluation due to data, evaluation methodology and capacity constraints. Existing rural road safety research in Ethiopia have mainly focused on overall crash frequencies and trends (Abegaz & Gebremedhin, 2018), with limited methodological depth to understand the outcome concerning the severity of heavy truck crashes .

The methods of analysis used in those studies have been dominantly based on descriptive statistics or traditional regression analysis, without much use of sophisticated models of severity and risk assessment. Specifically, the integration of ordinal models of severity and Empirical Bayes methods to address jointly the impacts of crash severity factors and the concentration of risk associated with infrastructure in the Ethiopian situation has not been investigated well (Hareru, Negassa, Abebe, et al., 2022).

Moreover, in spite of the fact that the Adama-Awash corridor plays a crucial role in national and international freight transport, no safety analyses undertaken on this corridor and not conducted any freight related crash characteristics in y discernible fashion, segment-level freight-related risk identification, thus limiting safety prioritization and corresponding countermeasure development catering to heavy trucks on the dedicated corridor. Consequently, there is a need for integrated research studies that, cumulatively, test for: model crash severities involving heavy trucks using appropriate ordinal techniques, identify high-risk roadway segments using Empirical Bayes techniques, and Contextualize findings within a major freight corridor. This research bridges the existing knowledge gaps with a truck-centered and methodologically integrated safety analysis suited to the Adama-Awash corridor in order to make a constructive contribution to the subject matter of freight transport road safety policy.

CHAPTER THREE

DATA AND METHODOLOGY

3.1. Introduction

Road safety is a global concern and a comprehensive data is required to make significant analyses. It is pertinent to ensure that primary and secondary sources are employed in conducting the study in an attempt to understand the different concerns associated with road safety. The basis for conducting the study is laid by the data compiled from different offices. However, the obtained data needed to be verified and organized before being used for analysis. To do that a check list was prepared in order the select and verify necessary data.

Several key factors influence road safety, including traffic and road characteristics, infrastructure-related risk factors, environmental and driver conditions, and human factors. Road and traffic features like speed, congestion, and road curvature can affect road safety in different ways, necessitating more research to create safety regulations that work. Infrastructure-related risk factors, such as alignment features, road surface deficiencies, and junction deficiencies, all of which are ranked based on their impact on crash risk, frequency, and severity. Environmental and driver conditions, including weather, road parameters, and driver conditions, significantly affect crash severity.

This study employed a combination of tools and methods, including Python, Google Earth Pro, Empirical Bayes (EB) using Negative Binomial Regression to predicted crash frequency, and Ordinal Logistic Regression for predicting and evaluating traffic crash severity and evaluate segment-level safety performance in Adama-Awash Road segment. The research focused on factors such as heavy truck type, Road Geometric Characteristics, environmental conditions that contribute to road crashes, including. Descriptive analysis was performed using Python to examine the factors associated with crashes. Python was also used to implement the Ordinal Logistic Regression model. Safety evaluation was conducted using the Empirical Bayes method.

Descriptive analysis was also conducted to assess overall crash trends and by combining these tools and methods, this study provides a comprehensive understanding of the various factors impacting road traffic safety.

3.2. Study Area

This study evaluates the road safety conditions of a critical trunk road segment within Ethiopia's Federal Road network. The segment stretches from Adama City in the Oromia region (8°44' N, 39°04' E) to Awash Sebat Kilo in the Afar region (8°58'59.99" N, 40°10'0.01" E), located in the eastern part of the country.

This study evaluates the road safety conditions of a critical trunk road segment within Ethiopia's Federal Road network. The road map illustrating the study area is provided below.

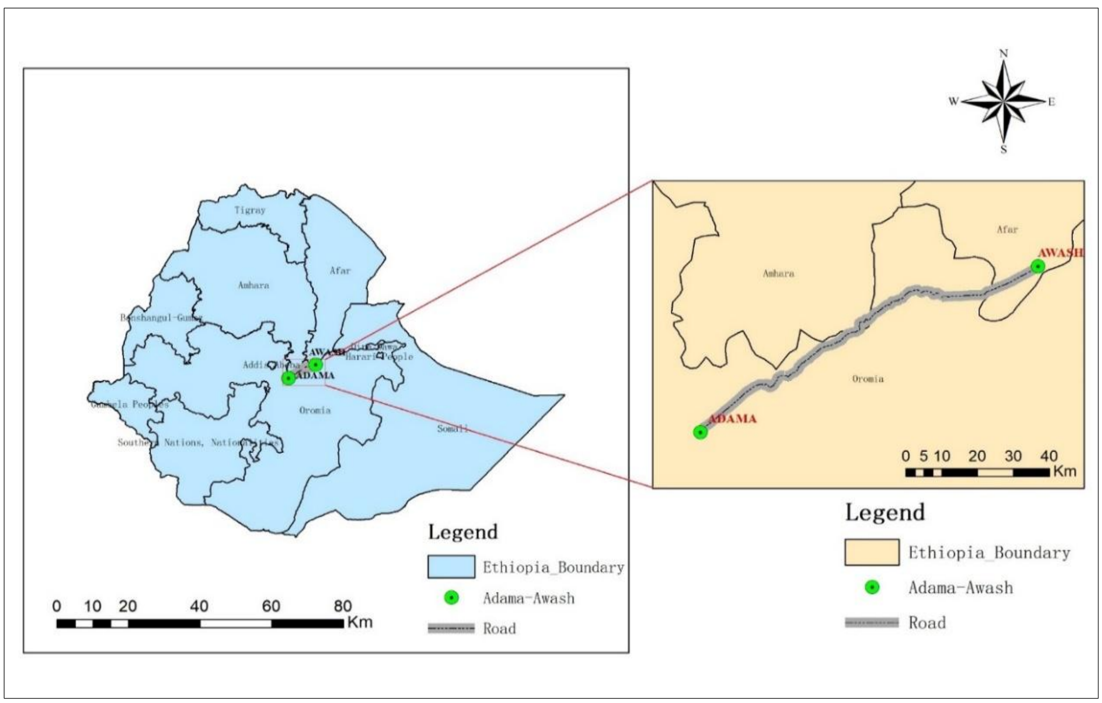

Figure 21: Adama-Awash Road segment alignment map

The road section is functionally classified as a trunk road. It experiences a high volume of mixed traffic, including heavy-duty vehicles such as heavy trucks and trailers, alongside passenger vehicles such as buses, minibuses, and private cars. The construction of this section of roadway dates back to several decades. Over the past years, it has undergone extensive maintenance interventions, including routine asphalt overlays and heavy repairs. These continuous efforts have generally maintained the pavement in a satisfactory condition. However, occasional problems, including potholes and surface deterioration, still occur often due to vehicle crashes and the significant stresses created by heavy traffic flows.

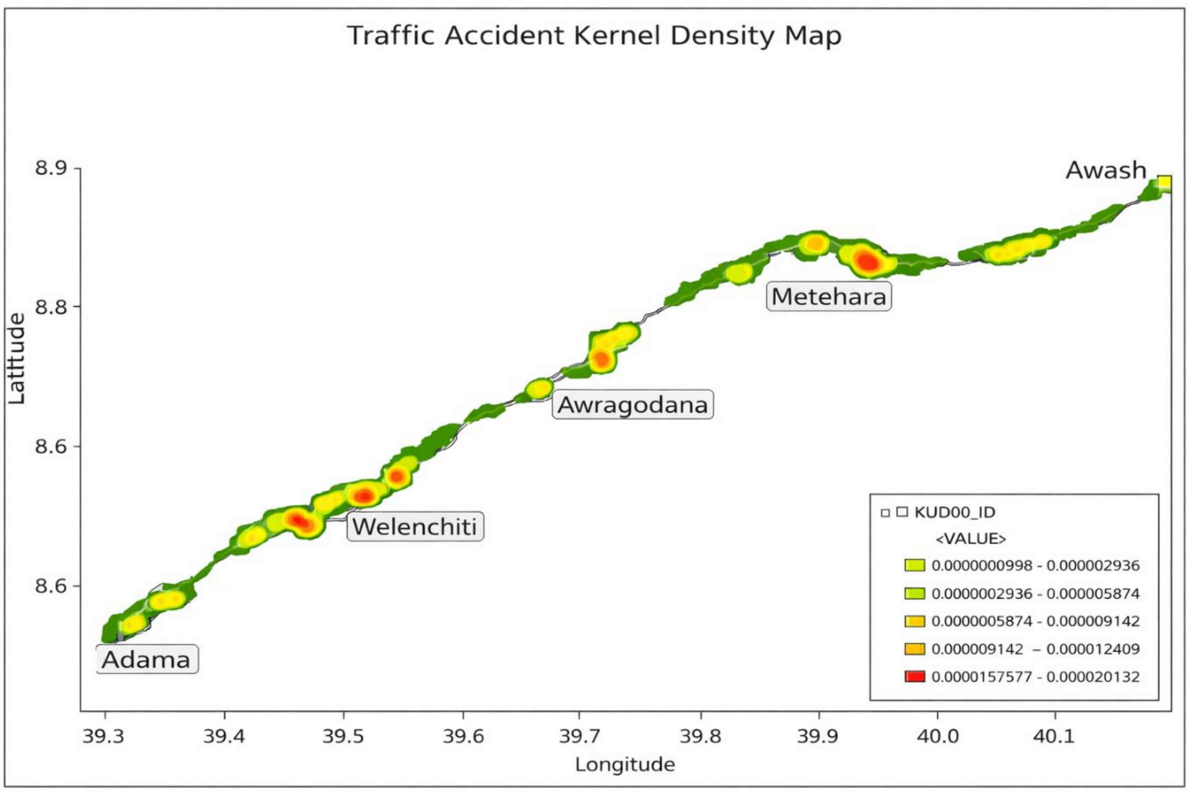

Figure 22: Traffic Accident kernel Density Map of Adama Awash Road segment

For this study, the Adama - Awash corridor was divided into four sub-segments as shown in Table 6 to enable segment-based safety evaluation. The segmentation was based on road environment (rural/town sections), traffic exposure (AADT), and geometric characteristics of the road, including the presence and extent of horizontal curves.

The Adama - Wolenchiti segment passes through rural villages and small towns and characterized by a relatively straight road alignment. The second section Wolenchiti - Awragodana mainly crosses rural areas and has the highest accident rate, as indicated in the spatial density map above figure 22 and has horizontal curves. The third section, Awragodana - Metehara includes sections with horizontal curves and has smaller curve radii compared to the Wolenchiti–Awragodana section, while Metehara - Awash passes through rural areas and the Awash National Park. This classification allows section-by-section analysis of crash patterns and safety performance along the corridor.

Table 6: Adama-Awash Road sub-segments

Segment	Segment Name	Chainage (km)	Length (Km)	*AADT*				
				2019	2020	2021	2022	2023
1	Adama-Wolenchite	0 - 20	20	9623	8923	9872	10237	10357
2	Wolenchite-Awragodana	20-52	32	8732	9218	9767	10234	10436
3	Awragodana-Metahara	52-80	28	8709	9400	9836	10987	10538
4	Metahara-Awash	80-120	40	8768	8967	9800	10867	10237

AADT Source: Ethiopian Road Authority (ERA), Dire Dawa Branch

3.3. Data collection and organization

To ensure the validity and reliability of research findings related to traffic crash severity on the Adama-Awash Road segment, this study gathered data on Annual Average Daily Traffic (AADT), traffic crash records, road geometric features, and environmental factors (e.g., weather conditions). As the quality of the final research outcomes is directly dependent on the accuracy and completeness of the collected data, careful attention was paid to data collection, organization, and filtering to ensure the highest level of data quality.

The target population of this study consists of heavy truck crashes occurring on major interurban freight transport corridors in Ethiopia, with national and Oromia regional aggregated crash data used solely to contextualize freight-related safety conditions at the macro level. The Adama Awash Road segment is chosen as a typical study location, as it is the main import export corridor approximately carrying out about 90% of Ethiopia's import-export function, and the traffic composition is dominated mainly by heavy trucks, as started in the AADT and crash record by vehicle type and severity.

For corridor-level analysis, a complete enumeration (census) approach was employed, whereby all 651 recorded crashes from 2019–2023 were included, of which 536 (82.3%) involved heavy trucks, eliminating sampling bias and making probability or convenience sampling unnecessary.

The adequacy of sample size in modeling severities is also validated through recognized standards in using Logistic Regression and Ordinal Regression,

3.3.1. Collecting and Organizing Relevant Data

Organized data were collected from the Road Safety and Insurance Fund Service at national level a five-year aggregated traffic crash data (2012 EC (2019/20) to 2016 EC (2023/24) by regional administration and Annual Average Daily Traffic (AADT), of five Major Economic Corridors Originating from Addis Ababa that is Addis - Bishoftu, Addis –- Debrebirhan, Addis - Holeta, Addis - Wolliso, Alemgena - Butajira and other main corridors Adama – Metehara-Awash and Addis Commando has been collected from Ethiopian Roads Administration.

For the Adama Awash Road corridor over 651 crash data records were collected for a five-year period (2019-2023). Importantly, 536 records (82.3%) of the dataset involve heavy vehicle traffic crashes and used for Analysis in this study. Additionally, the Average annual daily traffic (AADT) by segment level for the five years, the geometric characteristics, which show lane width, profile of the road, curve radius, Horizontal Alignments, and pavement condition, like the international roughness index (IRI), percentage of cracking, were collected by the Author from Ethiopian Road Administration Dire Dawa District.

3.3.2. Checklist Preparation and Data Verification

In this study, traffic crash records, traffic volume, and road characteristics data were collected by the author from different offices in Dire Dawa like Ethiopian Roads Administration Dire Dawa district, and Alemgena district and direct field measurement However, the collected data had gaps and irrelevant information. Therefore, the data was organized, cleaned, cross-checked, and analyzed before use. The first step in this process was to prepare a checklist.

Table 7: Checklist for Secondary Data Verification

s/ no.	Tasks to Examine	Verification	Measure and Outcome
1	Check the data source	Ensure the data is from a reliable source	The data is obtained from Ethiopian Roads Authority Dire Dawa District, which is a trusted source.
2	Confirm the data's time range	Ensure the data is up-to-date	Only crash data from the past 5 years is used, and older data is excluded.
3	Check for missing crash severity	Some records had missing values under “Crash Type”.	Records with missing crash severity were removed because severity is the dependent variable.
4	Check driver age completeness	A few records had blank or unrealistic driver ages (e.g., age = 8 or >100).	Such records were excluded from the severity analysis
5	Verify driver experience consistency	Some drivers had 5–10 years of experience but were aged below 20 years.	Inconsistent records were removed after logical verification.
6	Verify license experience relationship	Records showed drivers without licenses but with high driving experience.	These records were reviewed and excluded due to logical inconsistency
7	Validate spatial coordinates	Latitude and longitude values were plotted in Google Earth Pro.	Records falling outside the study corridor were removed from the dataset.
8	Check road condition consistency	Some crashes recorded “Good Light” during late-night hours (21:00–22:00).	These records were rechecked and corrected or excluded if unverifiable.
9	Final data readiness check	All independent variables were reviewed for completeness and coding.	The final cleaned dataset was confirmed suitable for ordinal logistic regression analysis.

This checklist ensures that all secondary data is thoroughly verified and prepared for reliable analysis, minimizing errors and enhancing the quality of research outcomes.

3.4. Variables Description

3.4.2. Independent Variable

Any factor thought to have a causal influence or contribute to the occurrence of a crash might be considered an independent variable in the context of traffic crashes. Hence, the following data are the independent variables used for the study analysis;

(1) Time of crash: Daytime, Night Time

(2) Day of the week: Weekdays, Weekends

(3) Zone: Adama, West Showa, East Shewa

(4) Driver's age: Young Adult (18-24), Early Adulthood (25-44), Middle Adulthood (45-59), Older Adults (60-74), Elderly (>74)

(5) Driver's education level: Elementary and Below, High school, Diploma, Bachelor's Degree

(6) Vehicle driver relationship: Employee Driver, Owner

(7) Heavy vehicle(truck) type: Trailer Truck, Articulated Trailer, Heavy Truck

(8) Vehicle Defects: Yes, No

(9) Driving License: Yes, No, Unknown

(10) Driving Experience (Years): 0 to 5, 6 to 10, 10 to 20, Above 20

(11) Geometric Road Character: Downhill, Sharp Curve, Slightly Curve, Straight and Flat Surface, Straight and Slightly Slope, Straight and Steep Slope, Uphill

(12) Light Condition: Good Light, No Light, Poor Light

(13) Visibility: Good Visibility, Poor Visibility, No Visibility

(14) Weather Condition: Cloudy, Cold, Foggy, Good Weather, Hot, Raining, Windy

(15) Primary Collision type: Animal Crash, Head on Crash, Pedestrian Crash, Rear End Crash, Rollover crash, side impact crash

(16) Number of Involved Vehicles in a crash: 1, 2, 3

(17) Road Surface: Dry, Wet, Other

(18) Pavement Surface condition: Good Asphalt, Cracked Asphalt

(19) Segment wise: 0-20 km, 20-52 km, 52-80 km, 80-120 km

(20) Segment based Average AADT: 0-20 km, 20-52 km, 52-80 km, 80-120 km

(21) Number of Horizontal curves by segment: 0-20 km, 20-52 km, 52-80 km, 80-120

3.4.3. Dependent Variables

The dependent variable in this research is Accident outcome. These variables are categorized based on severity levels, which include Property Damage, Slight Injuries, Serious Injuries, and Fatalities.

Table 8: Percentage of truck Crash Type

Severity	Number of crashes	Percent
Fatal	124	23.13
Serious Injury	59	11.01
Slight Injury	28	5.22
Property Damage	325	60.63
Total	**536**	**100**

Source: Ethiopian Road Administration (ERA), Dire Dawa Branch

Table 8 presents the crash data set divided into four severity categories. The crash data summarizes 536 incidents classified by severity: fatal crashes (124 cases, 23.13%), serious injury crashes (59 cases, 11.01%), slight injury crashes (28 cases, 5.22%), and property damage crashes (325 cases, 60.63%). The most common are property damage crashes. The second most frequent are fatal crashes, indicating a serious road safety issue. Because the segment is an important freight transport corridor with heavy truck loading, fatal crashes are more frequent than serious or slight injuries. In addition, serious injury cases are more numerous than slight injury cases, which is different from general urban traffic crash tendencies. This indicates that when crashes happen on this freight corridor, their severity could be much higher.

3.5. Research Approach

This study focused on investigating heavy truck crashes used descriptive and regression analysis (statistical modeling) methods. The purpose of descriptive analysis is to analyze data on traffic crashes, including, severity, temporal trends and contributing factors and the results are presented using tables, graphs, and charts. Additionally, data summarization and interpretation of key crash features, including numerical and categorical variables, have been conducted to explore how road geometry and surface conditions influence crash frequency and severity.

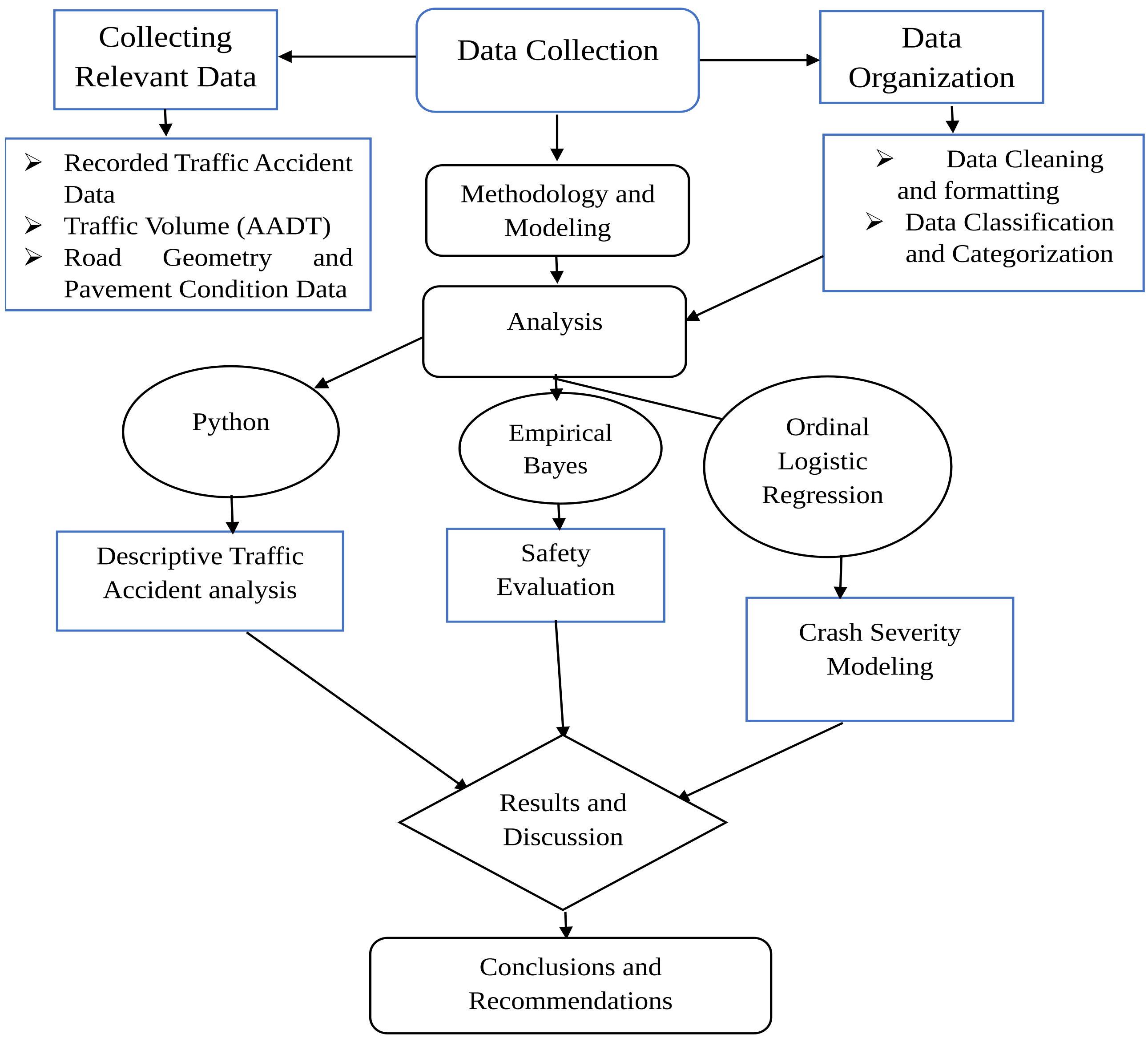

Figure 23: Flow chart diagram shows the process of methodology

This study employed a multi-method analytical framework combining statistical modeling, and safety performance evaluation.

Ordinal logistic regression (OLR) was employed to investigate contributing factors to heavy truck crash severity, such as road conditions, road geometric characteristics, driver behavior, vehicle characteristics, and environmental factors. A chi-square test (X^2), was first applied to determine and select significant variables (P value <0.05), Correlation and Collinearity Diagnostics conducted to check Correlation and Collinearity among independent variables using Variance Inflation Factor (VIF) and Tolerance (1/VIF). Then finally a brand test of parallel regression assumption was conducted to validate the proportional odds assumption for the independent variables before final model estimation. Then finally, the severity modeling was conducted by quantifying the relationship between the significant independent variables and the ordered categories of crash severity by determining the coefficient beta (β) using Python.

Finally, a safety assessment of the 120 km Adama Awash rural road segment was conducted by dividing the segment into four sections using the Empirical Bayes (EB) a well-established approach for rural road safety evaluations. The analysis incorporates Average Daily Traffic (AADT), geometric features (average curvature, lane width, slope, and sight distance), and pavement conditions (such as pavement age, cracking percentage, and International Roughness Index (IRI). A Negative Binomial (NB) regression model was then applied to predict crash frequencies across the road section forecast crashes for every section and a python tool was applied.

CHAPTER FOUR

RESULTS AND DISCUSSION

This chapter outlines an analysis of the data of traffic crashes, interpretations, and discussions on the results. On the basis of the research scope, the analysis focuses on examining the determinants of crash severity using the Ordinal Logistic Regression (OLR), and analyzing the frequency of crashes and high-risk zones on the Adama - Awash highway segment using the Empirical Bayes (EB) technique.

4.1. Descriptive Analysis of Highway Heavy Truck Crash Characteristics

This section provides a detailed description of heavy truck crashes characteristics of the Adama Awash freight corridor based on time of day, type of heavy truck, demographic characteristics, environment, geometric characteristics of the road, and pavement conditions. Key elements of the analysis include:

(1) Temporal characteristics

I. Day of the Week: Crashes are Categorizing by the day of the week to determine which days have higher crash rates.

II. Time of Day: Analyzing crashes by time of day (e.g., morning rush hours, afternoon, night) to identify peak periods for crashes.

(2) Heavy truck characteristics

I. Truck Type: Categorizing crashes by Heavy truck type (e.g., Articulated Trailer, trucks, Trailer)

II. Truck defect: Indicating whether a truck defect was present at the time of the crash (Yes/No).

(3) Demographic Characteristics

I. Age Group: Analyzing the age groups of drivers involved in crashes to determine which age groups are most affected.

II. Driver Gender: Analyzing the gender of drivers involved in crashes to identify any gender-specific trends.

III. Educational level: Considering the educational background of drivers to explore its relationship with crash involvement.

IV. Driver Experience: Examining the driving experience of those involved in crashes to see if less experienced drivers are more prone to crashes.

(4) Environmental and Road Characteristics and Conditions

I. Roadway Characteristics: Information on road geometry (e.g., curvature, gradient, lane width), pavement type, road surface condition, horizontal Curves Radius

II. Pavement Condition: Classifying the road surface condition at the crash location (e.g., Good Asphalt, Cracked Asphalt) to evaluate its influence on crash frequency and severity.

III. Light Condition: Analyzing the light conditions (e.g., daylight, dusk, night) at the time

IV. Visibility: Assessing the visibility conditions (e.g., clear, foggy, rainy) during crashes to determine its role in traffic incidents.

V. Weather Condition: Examining weather conditions (e.g., sunny, rainy, snowy) at the time of crashes to identify weather-related risks.

VI. Crash Type: Categorizing crashes by crash type (e.g., rear-end and side-impact)

VII. Collision Type: Analyzing the type of collision (e.g., vehicle-vehicle, vehicle-pedestrian, vehicle-object) to identify patterns in collision dynamics.

The descriptive statistics includes frequency distributions, means, medians, modes, and standard deviations for each crash attribute. Visual representations such as bar charts, pie charts, heat maps, and line graphs are used to illustrate the data clearly, aiding in the identification of significant patterns and correlations. This comprehensive analysis helps stakeholders develop targeted strategies to reduce traffic crashes, enhance highway safety, and implement more effective road safety measures.

Table 9: Description of heavy vehicle crashes (2019- 2023)

Variables	Fatal crashes		Serious Injury		Slight Injury		Property Damage only		Total	
	Count	% age	Count	% age	Count	% age	Count	% age	Count	% age
Time										
Daytime	69	55.65	33	55.93	13	46.43	190	58.46	305	56.90
Nighttime	55	44.35	26	44.07	15	53.57	135	41.54	231	43.10
Sub total	124	100	59	100	28	100	325	100	536	100
Day of the week										
Weekdays	83	66.94	45	76.27	19	67.86	224	68.92	371	69.22
Weekends	41	33.06	14	23.73	9	32.14	101	31.08	165	30.78
Sub total	124	100	59	100	28	100	325	100	536	100
Driver's age										
Young Adult (18-24)	22	17.74	13	22.03	5	17.86	35	10.77	75	13.99
Early Adulthood (25-44)	92	74.19	42	71.19	21	75.00	254	78.15	409	76.31
Middle Adulthood (45-59)	8	6.45	4	6.78	2	7.14	26	8.00	40	7.46
Older Adults (60-74)	2	1.61	0	0.00	0	0.00	7	2.15	9	1.68
Elderly (>74)	0	0.00	0	0.00	0	0.00	3	0.92	3	0.56
Sub total	124	100	59	100	28	100	325	100	536	100
Driver's education										

level										
Elementary and below	36	29.03	26	44.07	15	53.57	109	33.54	216	40.30
High school	76	61.29	27	45.76	11	39.29	199	61.23	283	52.80
Diploma	10	8.06	4	6.78	1	3.57	11	3.38	26	4.85
Bachelor	2	1.61	2	3.39	1	3.57	6	1.85	11	2.05
Sub total	124	100	59	100	28	100	325	100	536	100
Driver's Action at the time of the crash**.**										
Changing lanes	1	0.81	0	0	0	0	1	0.31	2	0.37
Moving straight	79	63.71	34	57.63	12	42.86	175	53.85	300	55.97
Overtaking	31	25	22	37.29	16	57.14	112	34.46	181	33.77
Reversing	3	2.42	0	0.00	0	0.0	5	1.54	8	1.49
Stopping	5	4.03	2	3.39	0	0.0	7	2.15	14	2.61
Turning Right	5	4.03	1	1.69	0	0.0	25	7.69	31	5.78
Sub total	124	100	59	100	28	100	325	100	536	100
Vehicle driver relationship										
Employee Driver	103	83.06	49	83.05	18	4.10	269	61.28	439	81.90
Owner	18	14.52	6	10.17	7	8.75	49	61.25	80	14.93
Other	3	2.42	4	6.78	3	17.65	7	41.18	17	3.17
Sub total	124	100	59	100	28	30.497287	325	163.702097	536	100
Heavy vehicle(truck)										

type										
Trailer	71	57.26	30	50.85	15	53.57	174	53.54	290	54.10
Articulated Trailer	19	15.32	8	13.56	4	14.29	54	16.62	85	15.86
Truck	34	27.42	21	35.59	9	32.14	97	29.85	161	30.04
Sub total	124	100	59	100	28	100	325	100	536	100
Vehicle Defects										
Yes	9	7.3	2	3.4	2	7.1	18	5.5	31	5.8
No	107	86.3	53	89.8	23	82.1	274	84.3	457	85.3
Unknown	8	6.5	4	6.8	3	10.7	33	10.2	48	9.0
Sub total	124	100	59	100	28	100	325	100	536	100
Driving Experience (Years)										
0 to 5	71	58.2	29	50.0	16	57.1	139	42.8	255	47.75
6 to 10	29	23.8	19	32.8	6	21.4	104	32.0	158	29.59
10 to 20	23	18.9	10	17.2	4	14.3	65	20.0	102	19.10
Above 20	0	0.0	0	0.0	2	7.1	17	5.2	19	3.56
Sub total	123	100.0	58	100	28	100	325	100.0	534	100
Geometric Road Character										
Downhill	4	3.2	1	1.7	1	3.6	14	4.3	20	3.7
Sharp Curve	3	2.4	6	10.2	2	7.1	3	0.9	14	2.6
Slightly Curve	24	19.4	9	15.3	5	17.9	52	16.0	90	16.8
Straight and Flat Surface	83	66.9	41	69.5	17	60.7	218	67.1	359	67.0
Straight and	1	0.8	0	0.0	0	0.0	18	5.5	19	3.5

Slightly Slope										
Straight and Steep Slop	1	0.8	0	0.0	0	0.0	2	0.6	3	0.6
Uphill	8	6.5	2	3.4	3	10.7	18	5.5	31	5.8
Sub total	124	100.0	59	100	28	100	325	100	536	100
Light Condition										
Good Light	59	47.6	34	57.63	21	75	209	64.3	323	60.3
No Light	42	33.9	16	27.12	5	17.9	72	22.2	135	25.2
Poor Light	23	18.5	9	15.25	2	7.1	44	13.5	78	14.6
Sub total	124	100	59	100	28	100	325	100	536	100
Visibility										
Good Visibility	64	51.6	34	57.6	21	75	207	63.7	326	60.8
Poor Visibility	22	17.7	10	16.9	2	7.1	46	14.2	80	14.9
No Visibility	38	30.6	15	25.4	5	17.9	72	22.2	130	24.3
Sub total	124	100	59	100	28	100	325	100	536	100.0
Weather Condition										
Cloudy	8	6.5	3	5.1	0	0	5	1.5	16	3.0
Cold	4	3.2	5	8.5	0	0	10	3.1	19	3.5
Foggy	1	0.8	0	0.0	0	0	3	0.9	4	0.7
Good Weather	78	62.9	41	69.5	22	78.6	197	60.6	338	63.1
Hot	21	16.9	8	13.6	3	10.7	70	21.5	102	19.0
Raining	6	4.8	0	0.0	3	10.7	11	3.4	20	3.7
Windy	6	4.8	2	3.4	0	0	29	8.9	37	6.9
Sub total	124	100.0	59	100	28	100	325	100.0	536	100.0

Primary Collision type										
Animal Crash	0	0.0	0	0.0	0	0.0	29	8.9	29	5.4
Head On Crash	45	36.3	17	28.8	6	21.4	73	22.5	141	26.3
Pedestrian Crash	41	33.1	15	25.4	6	21.4	0	0.0	62	11.6
Rear End Crash	4	3.2	11	18.6	6	21.4	44	13.5	65	12.1
Rollover crash	31	25.0	16	27.1	9	32.1	127	39.1	183	34.1
Side impact crash	3	2.4	0	0.0	1	3.6	52	16.0	56	10.4
Sub total	124	100.0	59	100	28	100	325	100.0	536	100.0
Number of Involved Vehicles										
1	72	58.1	29	49.2	17	60.71	198	60.9	316	59.0
2	49	39.5	22	37.3	11	39.29	110	33.8	192	35.8
3	3	2.4	7	11.9	0	0.00	17	5.2	27	5.0
6	0	0.0	1	1.7	0	0.00	0	0.0	1	0.2
Sub total	124	100.0	59	200	28	100.00	325	100.0	536	100.0
Road Surface										
Dry	103	83.1	55	93.2	16	57.14	290	89.2	464	86.6
Wet	18	14.5	4	6.8	11	39.29	34	10.5	67	12.5
Other	3	2.4	0	0	1	3.57	1	0.3	5	0.9
Sub total	124	100.0	59	100	28	100.00	325	100.0	536	100.0
Pavement Surface condition										

Good Asphalt	115	92.7	58	98.3	25	89.29	306	94.2	504	94.0
Cracked Asphalt	9	7.3	1	1.7	3	10.71	19	5.8	32	6.0
Sub total	124	100.0	59	100.0	28	100.00	325	100.0	536	100.0
Segment Wise										
0-20 Km	23	18.5	14	23.7	6	21.43	65	20.0	108	20.1
20- 52 Km	40	32.3	18	30.5	5	17.86	85	26.2	148	27.6
50 -80 Km	32	25.8	15	25.4	7	25.00	98	30.2	152	28.4
80-120 Km	29	23.4	12	20.3	10	35.71	77	23.7	128	23.9
Sub total	124	100.0	59	100.0	28	100.00	325	100.0	536	100.0

Table 10: Annual Crash Statistics and Traffic Volume by Segment along the Adama–Awash Road (2019–2023)

Segment	Year	AADT	Average Horizontal Curves Radius (m)	Fatal	Serious Injury	Slight Injury	Property Damage	Total Crash
0-20 km	2019	9623	350	3	1	0	3	7
	2020	8923		3	2	0	4	9
	2021	9872		7	3	3	13	26
	2022	10237		10	3	4	19	36
	2023	10357		8	4	3	17	32
20-52km	2019	8732	260	2	2	0	11	15
	2020	9218		4	1	0	14	19
	2021	9767		8	3	1	17	29
	2022	10234		7	5	3	31	46
	2023	10436		9	5	0	25	39
52-80 km	2019	8709	320	0	1	0	3	4
	2020	9400		3	4	0	6	13
	2021	9836		7	5	2	23	37
	2022	10987		9	4	4	29	46
	2023	10538		7	3	1	21	32
80-120 km	2019	8768	360	2	1	0	15	18
	2020	8967		6	2	0	9	17
	2021	9800		9	5	4	15	33
	2022	10867		12	2	1	20	35
	2023	10237		8	3	2	30	43
Total				124	59	28	325	536

For the matter of accuracy, the horizontal curve radius was also extracted from google earth pro using a Three-Point Geometry method. In this method, three points on the curve were identified and their (x, y) coordinates were measured: the Point of Curvature (PC), a midpoint on the curve, and the Point of Tangency (PT). The radius of the curve was then calculated using the coordinates of these three points using the following formula.

$$R = \frac{\sqrt{\sqrt{[(a^2+b^2)(c^2+d^2)(e^2+f^2)]}}}{2\,|\,x_1(y_2-y_3)+x_2(y_3-y_1)+x_3(y_1-y_2)\,|} \qquad \textit{Equation 10}$$

where:

$a = x_2 - x_1$, $b = y_2 - y_1$

$c = x_3 - x_2$, $d = y_3 - y_2$

$e = x_1 - x_3$, $f = y_1 - y_3$

4.1.1. Characteristics of Heavy Truck Crashes

4.1.1.1. Demographic Characteristics

Table 11 shows the descriptive analysis of driver (demographic) characteristic of the crashes on the segment.

Table 11: Demographic Characteristics of Recorded Truck Crashes

Driver Characteristics		Frequency	Percentage
Gender			
	Male	536	100
	Female	0	0
	Total	536	100
Age			
	18-24	75	13.99
	25-44	409	76.31
	45-59	40	7.46
	60-74	9	1.68
	>74	3	0.56
	Total	536	100
Driver Vehicle Relationship			
	Employee	439	81.9
	Owner	80	14.93
	Other	17	3.17
	Total	536	100

The age group of the drivers has been categorized based on the World Health Organization's (WHO) guidelines, which define the age groups as follows: 18-24 years as young adult, 25-44 years as early adulthood, 45-59 years as middle adulthood, 60-74 years as older adults, and 74 years and above as elderly. As stated in table 9, early adulthood drivers account for the largest share of crashes across all severity levels, contributing 74.19% of fatal crashes, 71.19% of serious injuries, 75.00% of slight injuries, and 78.15% of property-damage-only crashes. Young adult drivers also contribute notably to all crash types, particularly fatal and serious injury crashes, where they represent 17.74% and 22.03% of the total respectively. Due to the absence of data on the age distribution of licensed drivers, the proportion of accidents could not be compared with crash rates per driver. The high proportion of accidents among drivers aged 25–44 does not necessarily indicate a higher risk per driver; rather, it likely reflects greater driving exposure. Early adulthood (approximately 25–44 years) is widely recognized as the most economically active and productive phase of the life course, characterized by high labor-force participation and increased social and economic responsibilities. International labor statistics identify individuals aged 25–64 as the core working-age population, with participation in employment rising sharply after age 25 as most individual's complete education and enter stable careers((OECD), 2023). Because of this strong engagement in employment and household responsibilities, adults within this age group exhibit higher levels of daily mobility and travel demand, particularly for work-related commuting and other productive activities(Metz, 2010). Empirical studies on travel behavior consistently show that economically active adults undertake more frequent trips and longer commuting distances than adolescents and older adults, reflecting their dominant participation in the labor market and urban economic activities. Consequently, the 25–44 age cohorts is commonly identified in transport and public-health literature as the group that spends the greatest amount of time driving or commuting for work and related activities, highlighting the close relationship (Habib & Hui, 2017; Yang et al., 2018).

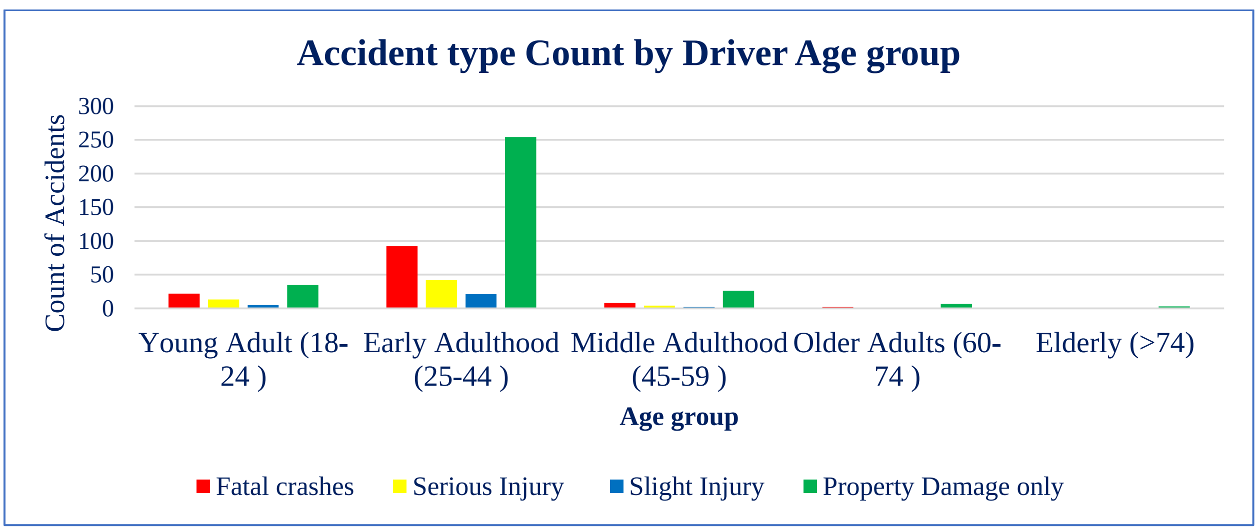

Figure 24: Crash outcome distribution by driver age

The data suggests all proportion of crashes involving male drivers. This observation aligns with the general trend of male dominance in the freight transport.

Table 12: Crash outcome percentage based on driver's educational level

Educational level	Fatal		Serious Injury		Slight Injury		Property Damage	
	Count	Percentage	Count	Percentage	Count	Percentage	Count	Percentage
Elementary and below	36	29.03	26	44.07	15	53.57	109	33.54
High school	76	61.29	27	45.76	11	39.29	199	61.23
Diploma	10	8.06	4	6.78	1	3.57	11	3.38
Bachelor	2	1.61	2	3.39	1	3.57	6	1.85
Masters	0	0	0	0	0	0	0	0

Drivers with high school education have the highest involvement in traffic crashes, account for the largest share of crashes across all severity levels, contributing 61.29% of fatal crashes, 45.76% of serious injuries, 39.29% of slight injuries, and 61.23% of property damage incidents. Following them, drivers with an elementary and below educational level have the second-highest crash record, accounting for 29.03% of fatal crashes, 44.07% of serious injuries, 53.57% of slight injuries, and 33.54% of property damage incidents.

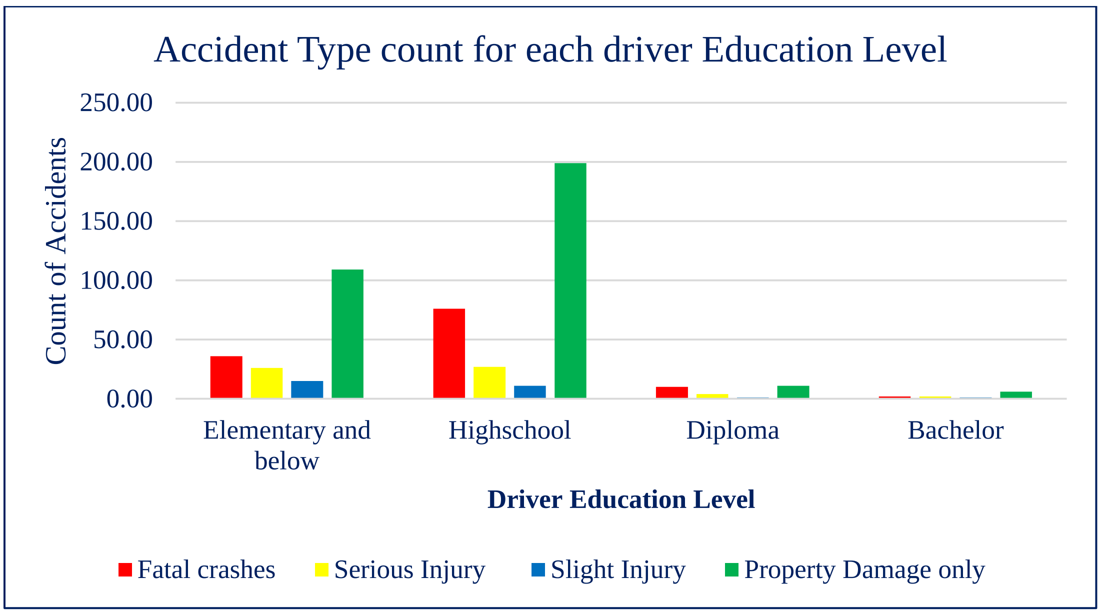

Figure 25. Crash outcome distribution by driver education level

The table below shows the percentage of traffic crashes contributed by drivers based on their years of driving experience:

Table 13: Traffic Crash Contribution by Driver Experience

Driving experience in Years	Fatal	Serious Injury	Slight Injury	*Property damage*
0 - 5	58.2	50	57.1	42.8
6 - 10	23.8	32.8	21.4	32
10 - 20	18.9	17.2	14.3	20
Above 20	0	0	7.1	5.2

From the analysis, drivers with 0-5 years of experience have the highest contribution to traffic crashes across all outcomes, including fatalities, serious injuries, slight injuries, and property damage. Drivers with 6-10 years of experience follow as the second highest contributors to traffic crashes.

As shown in figure 26 below, the data indicates that newer drivers (0-10 years of driving experience) are more frequently involved in crashes compared to those with more driving experience.

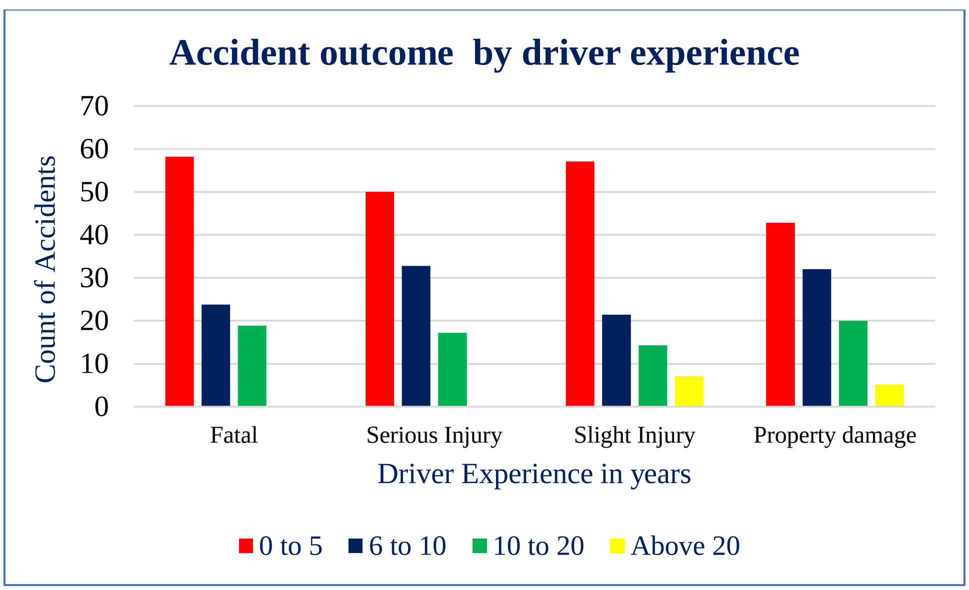

Figure 26: Crash outcome distribution by driving experience

Another important driver-related characteristic is the driver's action at the time of the crash. Figure 27, presents the distribution of crash severity by different driver actions, including changing lanes, moving straight, overtaking, reversing, stopping, and turning right.

As shown in the table, moving straight is the most frequently associated driver action across all crash severities. It accounts for 79 fatal crashes, 34 serious injury crashes, 12 slight injury crashes, and 175 property-damage-only crashes, indicating that a large proportion of crashes occur while drivers are proceeding straight along their lanes. These crashes are commonly related to rear-end collisions and vehicle rollovers.

The second most prominent driver action is overtaking, which contributes to 31 fatal crashes, 22 serious injury crashes, 16 slight injury crashes, and 112 property-damage-only crashes. Overtaking maneuvers are often associated with higher-risk situations such as head-on collisions, side impacts, rollovers, and pedestrian crashes.

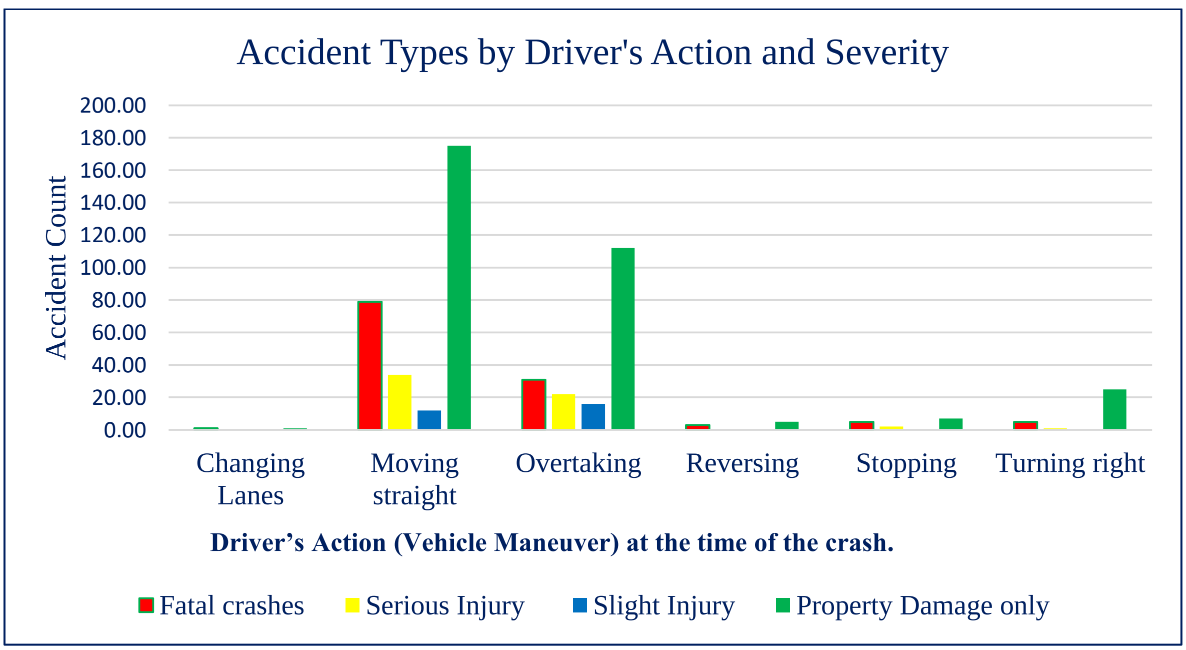

Figure 27: Crash outcome distribution by action of the driver

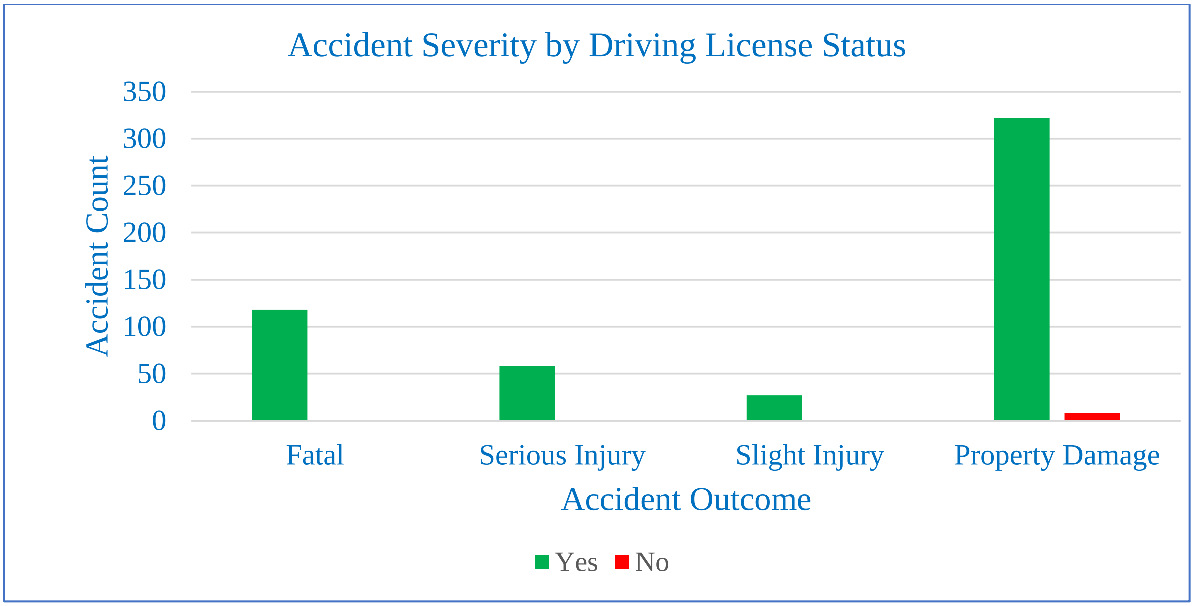

Figure 28: Crash outcome distribution by driving license status

The bar chart in figure 28 indicates that approximately 98% of the crashes involved drivers who possessed a valid driving license. This finding highlights the need for stronger follow-up measures, stricter enforcement of traffic regulations, and enhanced awareness programs for licensed drivers.

4.1.1.2. Truck Characteristics

In this study, Heavy trucks are categorized based on the vehicle classification of the American Association of State Highway and Transportation Officials (AASHTO, 2001). Heavy trucks are those trucks with a single rigid unit, typically 3–4 axles, and a length of about 9–12 m, designed to carry freight without a separate trailer. Trailer trucks are those trucks with two units consisting of a truck pulling a full trailer; usually having 4–6 axles and a typical length of 15–20m. Articulated trailers are those trucks with a tractor–semitrailer combination connected through a fifth-wheel joint, generally with about 5 axles and a length of 18–23 m. These vehicle types generally have larger dimensions and higher gross vehicle weights (up to about 40 t), which can influence crash severity and roadway safety. From the histogram chart and table highlights that both heavy trucks and trailer trucks are the leading vehicle types in terms of all crash outcomes, including fatal crashes, serious injuries, slight injuries, and property damage.

Table 14: Crash counts by truck type

Vehicle Type	Fatal	Serious Injury	Slight Injury	Property Damage
Trailer Truck	71	30	15	174
Articulated Trailer	19	8	4	54
Heavy Truck	34	21	9	97

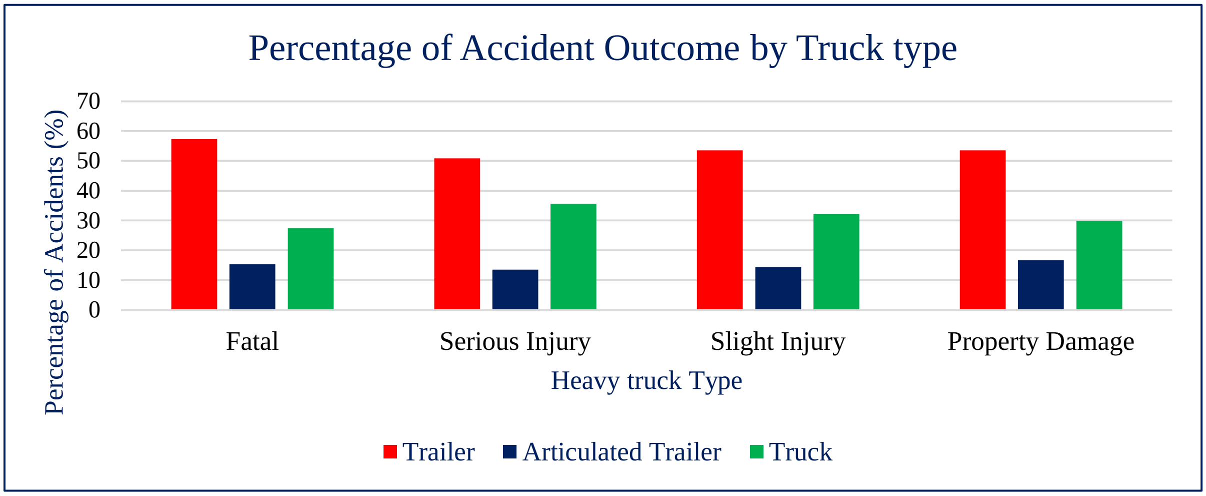

Figure 29: Crash percentage by truck type

Percentage of Crash Outcome by Truck type depicts that trailer trucks account for the highest share of fatal crashes (57.3%), which make them the main contributor to fatal crashes. they are followed by trucks (27.4%) and articulated trailers (15.3%). Trailers are also dominant across all severity levels, with over 50.85% of serious injuries, slight injuries, and property damage

Trucks play an important role in serious injuries (35.59%) and slight injuries (32.14%), indicating their overall safety concern. Articulated trailers, while involved in fewer fatal crashes, still account for 16.62% of property damage incidents, pointing to dangers associated with maneuverability and blind spots.

4.1.1.3. Road Geometry Characteristics

Table 15 presents the distribution of crash types across different road geometry characteristics. The classification of roadway geometry was developed based on the principles of horizontal and vertical alignment described in A Policy on Geometric Design of Highways and Streets (AASHTO, 2001).

In this study, roadway segments were categorized according to their horizontal curvature and vertical grade. Straight and flat surface refers to tangent sections with negligible longitudinal grade, while straight and slightly sloped sections represent tangents with a mild vertical grade. Uphill and downhill segments correspond to positive and negative roadway grades, respectively.

For horizontal alignment, curves were categorized as sharp curves and slightly curve. According to AASHTO geometric design principles (AASHTO, 2001), slight curves (or flat curves) are horizontal curves with relatively large radii that can operate with the normal crown cross slope without requiring significant super elevation. In contrast, the sharp curves are those curves with radii close to the minimum allowable radius for a given design speed which is calculated using the formula , $R_{min} = \frac{V2}{127(e+f)}$, where R is the minimum curve radius (m), V is the design speed (km/h), e is the superelevation rate, and f is the side friction factor.

Table 15:Crash Type Percentage for each Road Character

Road Character	Fatal	Serious Injury	Slight Injury	Property Damage
Downhill	4	1	1	14
Sharp Curve	3	6	2	3
Slightly Curve	24	9	5	52
Straight and Flat Surface	83	41	17	218
Straight and Slightly Slope	1	0	0	18
Uphill	1	0	0	2
Sum	124	59	28	325

Road alignment and profile is another important roadway-related factor influencing crash occurrence and severity. Table 15 and Figure 30 present the distribution of crash types across different road character categories, straight and flat road sections record the highest number of crashes, with 83 fatal, 41 serious injuries, 17 slight injuries, and 218 property-damage-only crashes. This is followed by slightly curved sections, which account for 24 fatal, 9 serious Lastly, Sharp curve and straight and slightly sloped roads report the lowest percentages across all categories, suggesting they might be less hazardous or less frequented, resulting in fewer crashes.

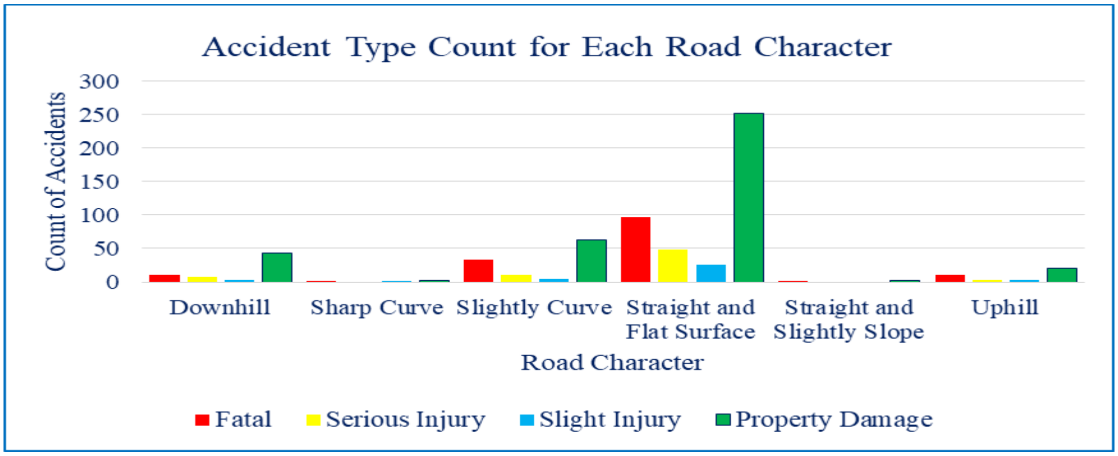

Figure 30: Crash outcome distribution by Road Character.

Overall, this data underscores the need for targeted road safety interventions, particularly on straight and flat surfaces and slightly curved roads, to mitigate crash risks and enhance overall safety.

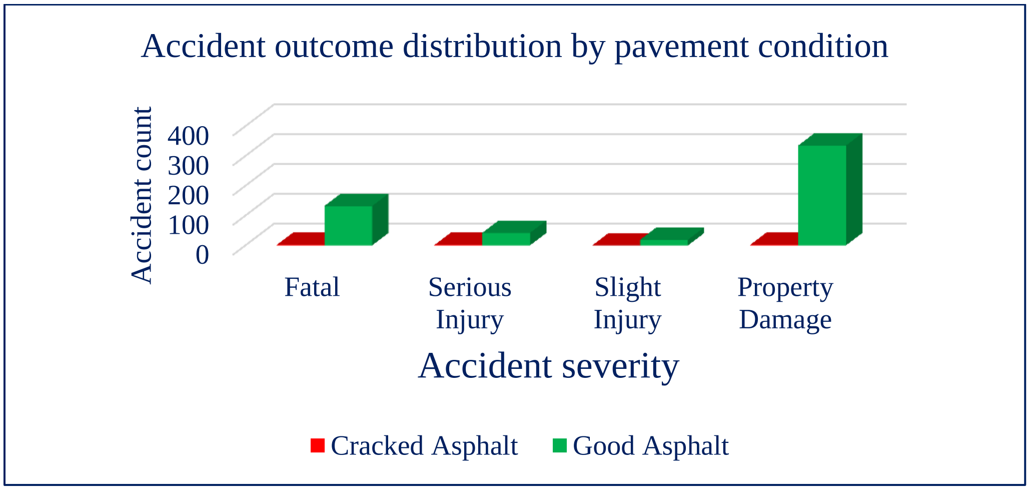

***Figure 31**: Crash outcome distribution by pavement condition*

For good asphalt, it emerges as the dominant pavement type for all crash categories, with a significantly high percentage of crashes occurring on this surface. Specifically, 92.7% of fatal crashes, 94.3% of property damage incidents, 98.3% of serious injuries, and 89.29% of slight injuries happen on good asphalt roads. This finding indicates that although asphalt roads are generally in good condition and provide better driving comfort, they account for the majority of crashes along the study corridor. This may be attributed to factors such as increased travel speeds and driver behavior. As observed from the road geometry analysis, most crashes occurred on straight and flat road segments, which may encourage higher vehicle speeds and reduce driver vigilance. Such roadway conditions can lead to decreased driver alertness, fatigue, or overconfidence, thereby increasing the likelihood of crashes despite the favorable pavement condition.

On the other hand, cracked asphalt accounts for a very small portion of the crashes, with only 7.3% of fatal crashes, 5.8% of property damage incidents, 1.7% of serious injuries, and none of the slight injuries occurring on this type of pavement. This indicates that while cracked asphalt contributes to crashes, it is less prone to causing severe crashes when compared to good asphalt.

4.1.1.4. Environmental and Road Surface Conditions

Environmental factors such as weather conditions, road surface conditions, light condition, visibility and built environment variables significantly impact traffic safety, with adverse conditions increasing the likelihood of crashes (Hammad et al., 2019).

(1) Light Condition

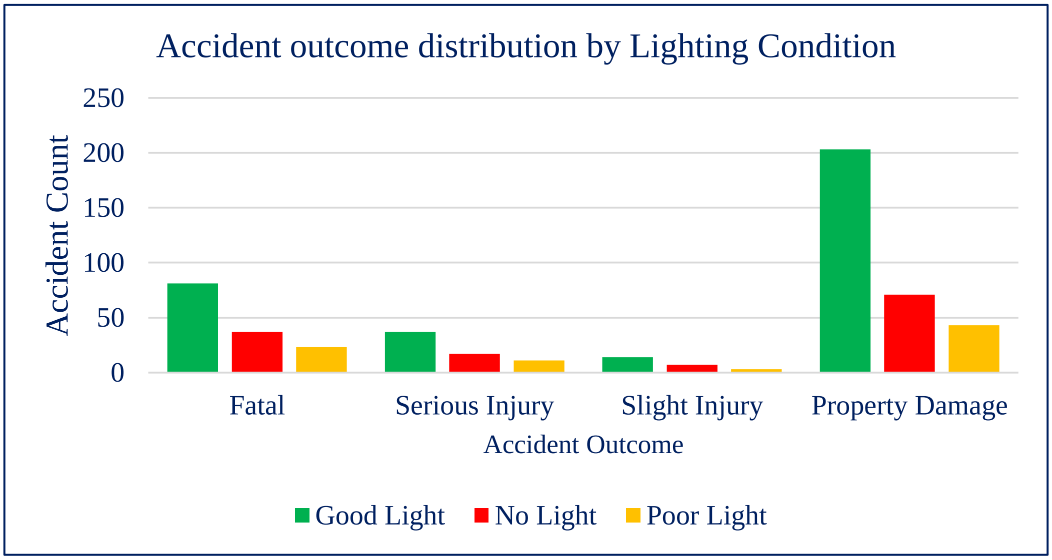

Figure 32: Crash outcome distribution by Lighting Condition

Light condition affects the visibility of the road, vehicles, objects, and other road users to drivers. From the bar chart, it is evident that the majority of crashes occur during good lighting conditions, with property damage being the most common outcome, followed by fatal crashes. Although crashes under poor light and no light conditions are relatively low in number, the severity of these crashes is notably higher. In particular, fatal and serious injury cases make up a significant proportion of the crashes that occur in no light and poor light conditions, despite their lower overall frequency.

(2) Weather Condition

The weather conditions considered in this study were classified based on the categories recommended in the Model Minimum Uniform Crash Criteria (MMUCC) ((NHTSA), 2017), a guideline that provides a standardized set of data elements for describing motor vehicle crashes. Accordingly, the weather conditions were grouped as cloudy, cold, foggy, good weather, hot, raining, and windy. As we can see from the Table 17 and Figure 34, the good weather shows the highest crash record across all categories, with 78 of Fatal, 41 of serious injury, 22 of slight injury and 197 of property damage. Next to the good weather condition, hot weather conditions, has high crash rate. Fatal crashes constitute 21 counts, 8 of serious injuries, 3 recorded of slight injuries and 70 crashes outcome of property damage incidents. These figures indicate a significant impact of hot weather on the severity of crashes, particularly fatal crashes, underscoring the necessity for tailored road safety measures to address the specific challenges posed by hot weather conditions.

Table 16: Crash Type Percentage for each Weather Condition

Weather Condition	Percentage			
	Fatal	Serious Injury	Slight Injury	Property Damage
Cloudy	8	3	0	5
Cold	4	5	0	10
Foggy	1	0	0	3
Good Weather	78	41	22	197
Hot	21	8	3	70
Raining	6	0	3	11
Windy	6	2	0	29

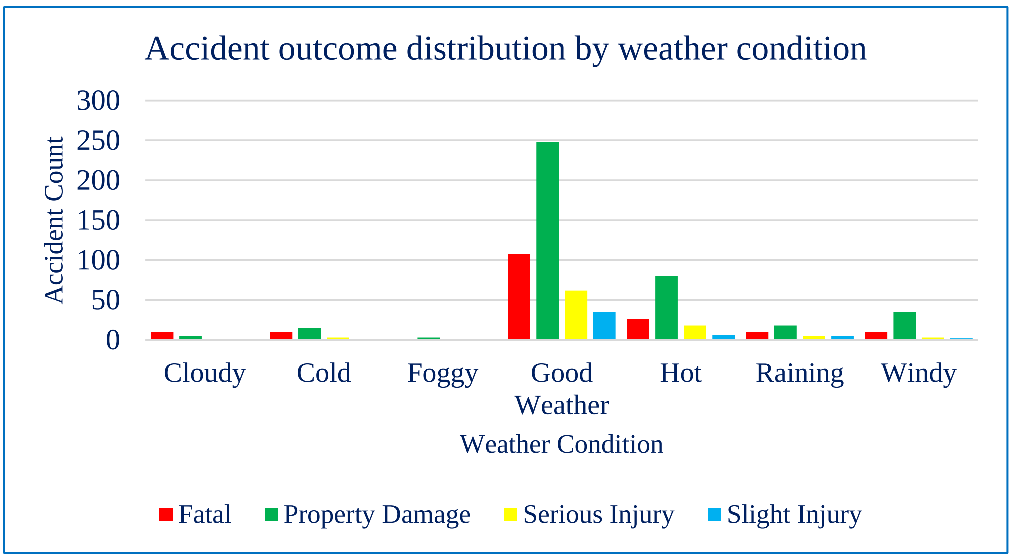

Figure 33: Crash outcome distribution by weather condition

Fatal crashes are significantly higher in good weather, emphasizing the need for enhanced road safety measures such as stricter speed regulations. Given these findings, road safety policies must prioritize preventive measures in high-risk weather conditions. In a cloudy and raining weather condition the fatal crash is high considering the frequency of the total crash in these weather conditions.

(3) Road Surface condition

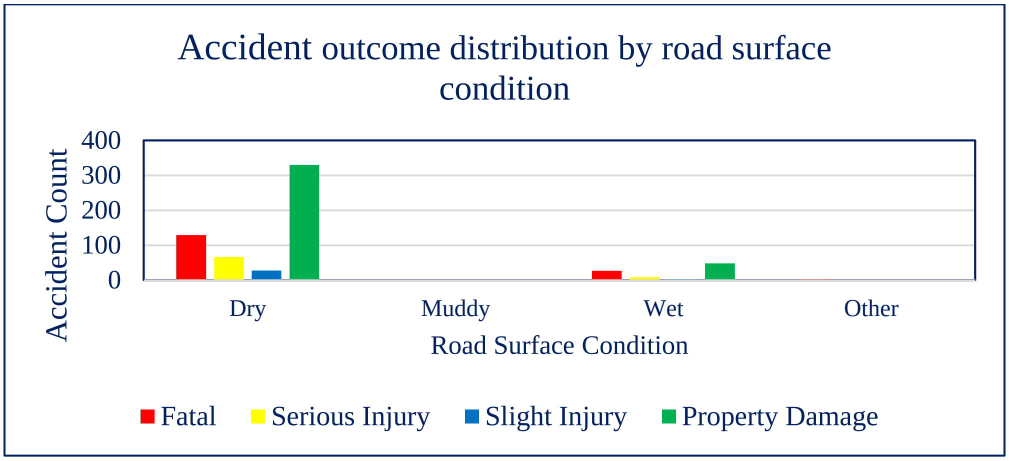

Figure 34: Crash outcome distribution by road surface condition

The other independent variable is Road surface condition and the classification is based on World Meteorological Organization (WMO) (Organization, 1969) , Which is classified as dry when no moisture is detected on the road surface, moist or damp when light moisture is present but does not significantly affect the road surface friction. The surface is classified as wet when a continuous film of water covers the road and classified as muddy when conditions include standing water greater than 3 mm, or when the surface is covered by snow, ice, or slush.

The traffic crash histogram, categorized by road surface conditions, indicates that the majority of crashes occur on dry asphalt surfaces.

(4) Collision Type

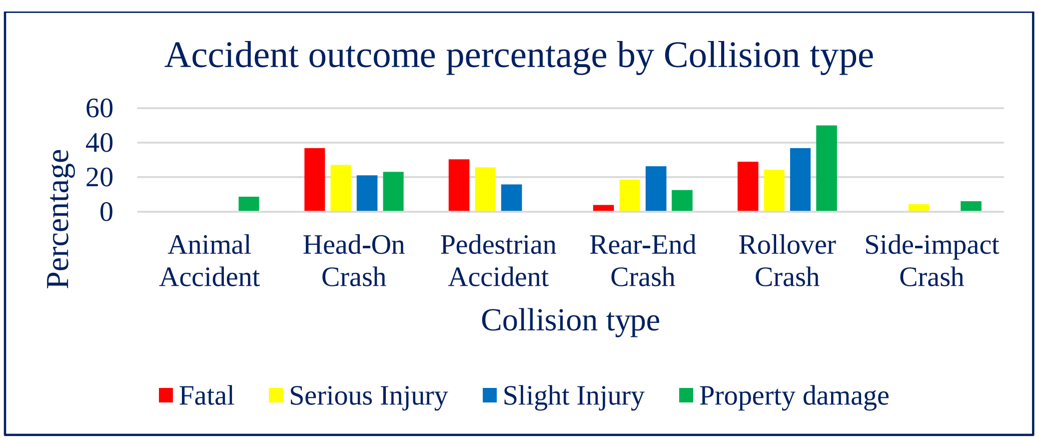

Figure 35: Crash outcome percentage by Collision type

Figure 35 indicate that head-on collisions have the highest fatality proportion (36.3%), followed by pedestrian collisions (33.1%). Rollover collisions predominate overall, causing 25% of fatal collisions, 39.1% of property damage, 27.1% of serious injuries, and 32.1% of slight injuries presumably due to heavy freight traffic and overloading on the Adama–Awash corridor. Rear-end collisions contribute most to property damage (13.5%) and slight injuries (21.4%), while side-impact collisions are relatively low. Animal-related collisions cause 8.9% of property damage but no injuries or fatalities.

4.1.1.5. Temporal and Spatial Characteristics

Figure 36 presents the percentages of different crash severity types (fatal, property damage, serious injury, slight injury) differ across the weekdays, showing some interesting trends:

Fatal crashes were highest on Monday (31.25%), with smaller percentages on Tuesday (19.77%) and Friday (21.51%). Serious injuries reached a peak in the middle of the week, particularly on Wednesday (13.4%) and Thursday (12.63%). Slight injuries were most numerous on Friday (7.53%), with the lowest proportion on Saturday (2.38%). Property damage crashes were most numerous on Tuesday (62.79%) and Thursday (61.05%), with the smallest proportion on Monday (56.25%).

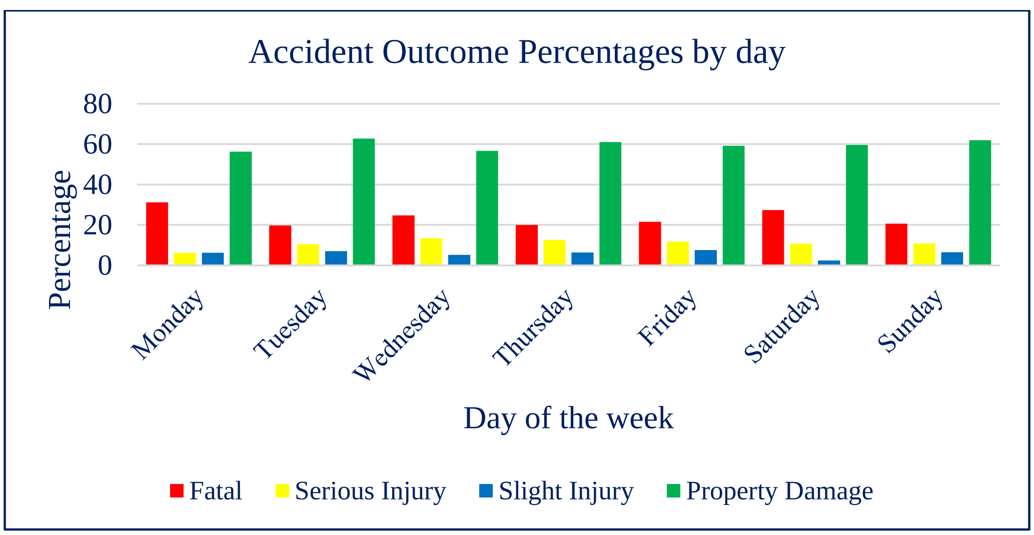

Figure 36: Crash distribution by day of the week

The overall trends of traffic crash show those weekdays (Monday through Friday) tend to have a higher percentage of serious injuries, while weekends have a higher proportion of fatal crashes and property damage incidents.

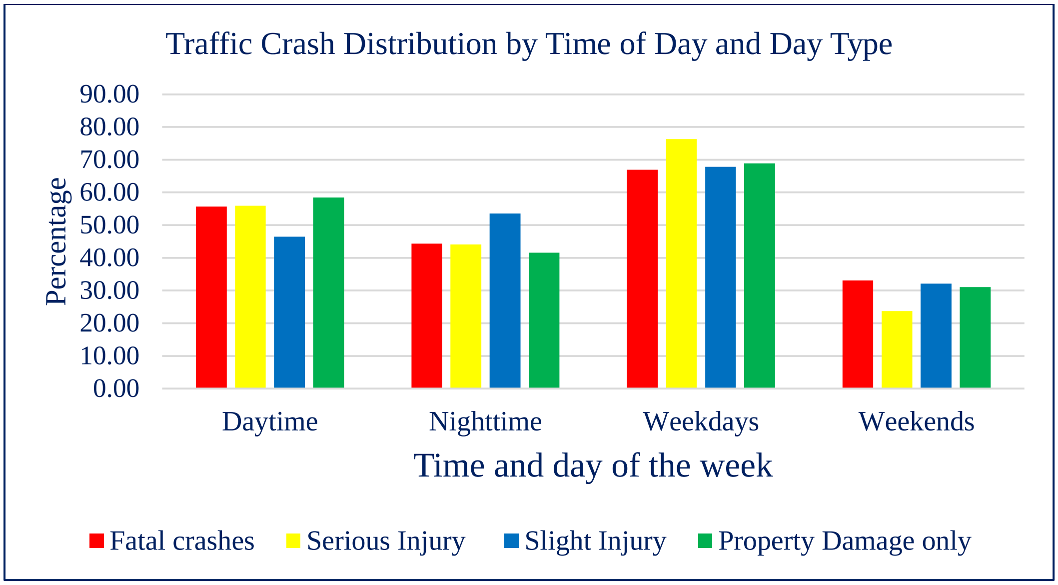

***Figure 37**: Traffic Crash Distribution by Daytime/Nighttime and Weekday/Weekend*

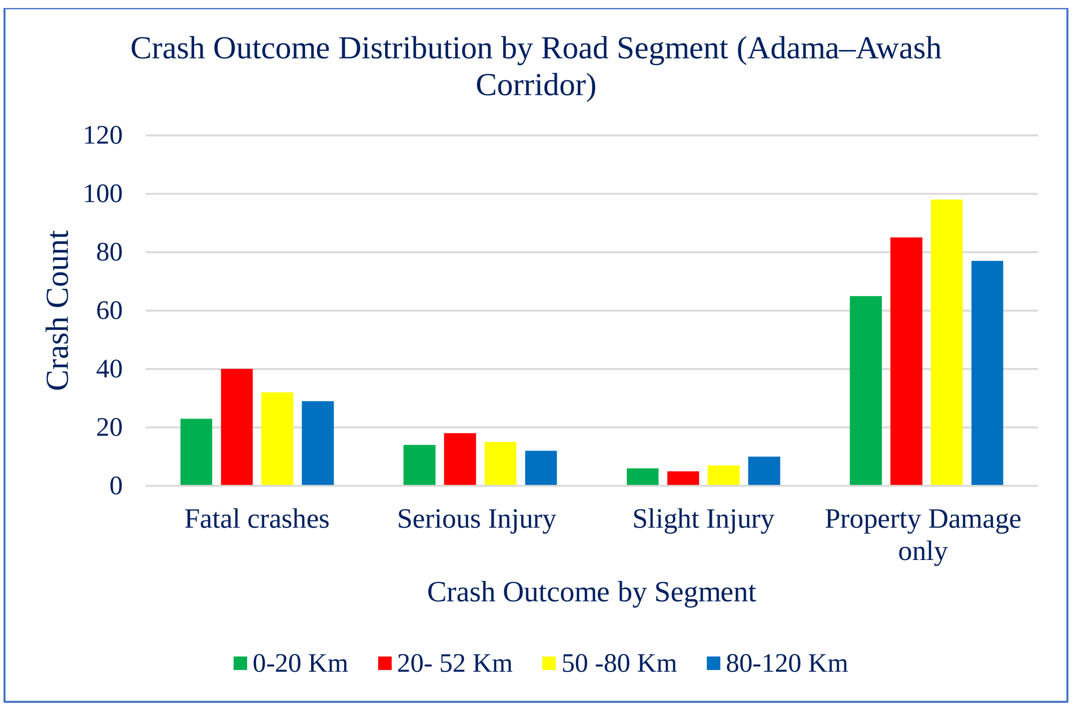

***Figure 38**: Crash Outcome Distribution by Road Segment (Adama–Awash Corridor)*

Figure 38, above shows that the road segments from Adama to Awash, specifically the 20-52 km and 52-80 km segments, have the highest crash rates, while the first 20 km segment from Adama has the lowest crash rate.

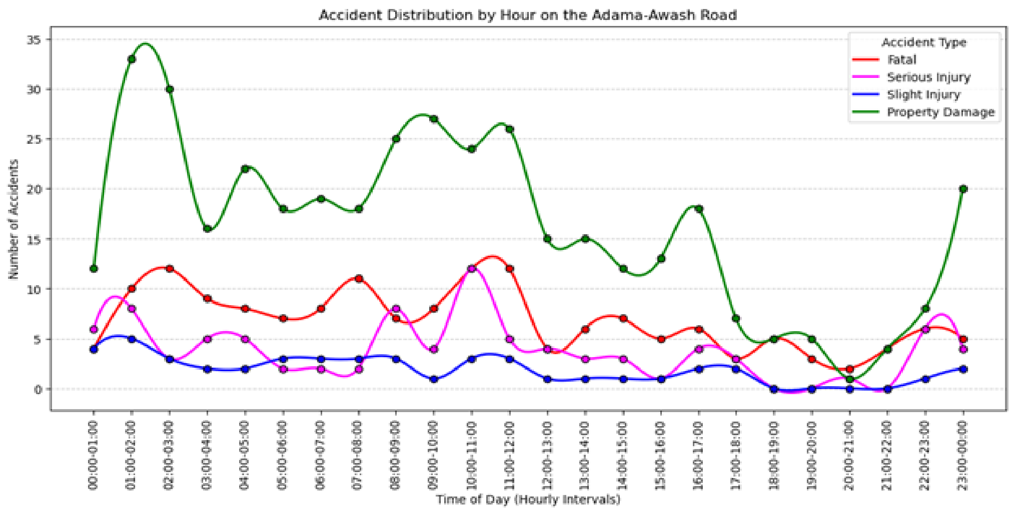

Figure 39: Hourly Distribution of Traffic Crashes

Figure 39 reveals some patterns in the occurrence of different crash types across various time intervals. Fatal crashes are most frequent between 11:00 AM to 12:00 PM, followed closely by 10:00 AM to 11:00 AM, highlighting a peak in severe crashes during the late morning hours. Serious injury crashes are most common during the early to mid-morning, with the highest frequency observed between 08:00 AM to 09:00 AM and 10:00 AM to 11:00 AM, indicating that these times may be particularly hazardous for more severe crashes. Slight injuries are most prevalent between 01:00 AM to 02:00 AM, showing a significant concentration of less severe crashes in the early morning. In terms of property damage, the highest number of incidents occurs between 02:00 AM to 03:00 AM, followed by 01:00 AM to 02:00 AM, suggesting that the early hours of the day are particularly prone to property damage crashes. These trends offer valuable insights into the times when crashes, especially those resulting in fatalities, serious injuries, or property damage, are most likely to occur.

4.2. Severity Modeling

4.2.1. Statistical analysis

To choose the right independent variables for the Ordinal logistics regression model, the first step is performing a Chi-square test (X2) of independence between crash outcomes and the independent variables, and a P- Value has been used to test a statistically significant association with crash outcomes. Variables with $p < 0.05$ show significant association whereas $p \geq 0.05$ show weak (no association) with the dependent variables. Then, factors related to road crashes that had shown a high correlation with crash severity levels were examined using an ordinal logistic regression model. The result of the significance level has presented table 18 below.

Table 17: Independent significant Variables included in the OLR model

S/ No.	Variable	Chi-square (X^2)	df	Sig (p-value)	Remark
1	Zone	48.96	6	0.000	Significant
2	Driver's Action	64.778	21	0.000	Significant
3	Primary Collision type	178.995	18	0.000	Significant
4	Driver Experience (Years)	25.006	9	0.003	Significant
5	Road Surface	17.88	6	0.0065	Significant
6	Driver Vehicle Relation	21.6	9	0.0102	Significant
7	Number of Involved Vehicles	18.732	9	0.0276	Significant
8	Weather Condition	37.938	24	0.0352	Significant
9	Truck Type	16.024	9	0.0264	Significant
10	Visibility	11.784	6	0.067	Not Significant
11	Vehicle Defects	14.748	9	0.0981	Not Significant
12	Light Condition	12.401	9	0.1916	Not Significant
13	Driver Education Level	15.756	12	0.2027	Not Significant
14	Pavement Surface condition	4.321	3	0.0288	Significant
15	Driver Age	12.488	12	0.0074	Significant
16	Geometric Road Character	15.446	18	0.0312	Significant
17	Day of the week	12.59	6	0.6584	Not Significant
18	Driving License	3.84	1	0.6925	Not Significant
19	Time of crash	*35.17*	*23*	*0.7043*	*Not Significant*
20	Road segment	13.85	12	0.0307	Significant
21	Horizontal curves radius	12.874	6	0.0208	Significant

The chi-square test results for the independent variables are shown in Table 18 above and using the Ordinal Logistic Regression model, the independent variables that exhibit a statistically significant relationship with the severity level of traffic crashes at the 5% significance level ($p < 0.05$) were chosen for additional examination. With p-values less than 0.05, the results show that fourteen (14) factors have a significant correlation with the severity of traffic crashes at the 5% significance level as presented in the table 18.

4.2.2. Brant Test of Parallel Regression

The outcome of the test on parallel regression assumptions in the ordinal logistic model, namely, the Brant test, is summarized in Table 18 below. The test provides a Chi-square value (X^2), degrees of freedom value (df), and corresponding probability value (p-value), all of which are returned for every independent variable.

Table 18: Brant Test of Parallel Regression Assumption

Variable	X^2	df	Probability (p-value)
Omnibus	333.584	135	0.06304
Number of Involved Vehicles	6.083	3	0.1076
Zone East Shewa	18.513	3	0.0603
Zone west Shewa	28.049	3	0
Zone_Adama	7.036	3	0.0715
Driver's Action Changing Lanes	17.929	3	0.0806
Driver's Action Overtaking	20.959	3	0.0601
Driver's Action Reversing	1.683	3	0.6407
Driver's Action Stopping	0.195	3	0.9784
Driver's Action Turning Right	0.777	3	0.855
Driver's Action moving straight	12.685	3	0.0504
Primary Collision type Head On Crash	12.872	3	0.0604
Primary Collision type Pedestrian Crash	77.022	3	0.0705
Primary Collision type Rear End Crash	16.645	3	0.0608
Primary Collision type Rollover crash	26.947	3	0.0807
Primary Collision type Side impact Crash	1.349	1	0.2455
Driver Experience (Years)_0 to 5	19.24	3	0.0707
Driver Experience (Years)_6 to 10	12.57	3	0.1057
Driver Experience (Years)_11 to 20	0.517	3	0.9151
Driver Experience (Years)_Above 20	3.387	3	0.3357
Road Surface Other	2.704	3	0.0396

Road Surface Wet	12.727	3	0.0503
Road Surface Dry	14.746	3	0.0743
Vehicle Driver Relation Owner	1.801	3	0.0147
Driver Vehicle Relation Employee Driver	0.597	3	0.8972
Weather Condition Cold	1.443	2	0.486
Weather Condition Foggy	0.018	3	0.0093
Weather Condition Good Weather	5.931	3	0.115
Weather Condition Hot	5.244	3	0.1548
Weather Condition Raining	4.303	3	0.2305
Weather Condition Windy	3.828	3	0.2807
Weather Condition Cloudy	0	3	1
Truck Type Trailer	4.384	3	0.2228
Truck Type Articulated Trailer	3.959	3	0.2659
Truck Type truck	8.146	3	0.0431
Pavement Surface condition Cracked asphalt	3.705	3	0.0624
Pavement Surface condition Good Asphalt	2.794	3	0.4244
Driver Age Elderly (>74)	0	3	0.0214
Driver Age Older Adults (60-74)	0.425	3	0.0306
Driver Age Middle Adulthood (45-59)	1.06	3	0.7867
Driver Age Young Adult (25-44)	5.981	3	0.1126
Driver Age Young Adult (18-24)	4.681	3	0.3054
Geometric Road Character Sharp Curve	5.571	3	0.1345
Geometric Road Character Slightly Curve	1.303	3	0.7285
Geometric Road Character Straight and Flat Surface	0.411	3	0.938
Geometric Road Character Straight and Slightly Slope	0.211	3	0.9758
Geometric Road Character Uphill	1.454	3	0.6929
Geometric Road Character curve	0	3	1
Geometric Road Character Downhill	2.056	3	0.0602
Segment 0-20 km	1.443	2	0.036
Segment 20-52 km	0.028	3	0.0793
Segment 52-80 km	4.921	3	0.125
Segment 80-120 km	6.204	3	0.448
Horizontal curve Radius (350m)	3.521	3	0.1134
Number of Horizontal curves (260m)	4.604	3	0.236
Number of Horizontal curves (320m)	1.56	3	0.218
Number of Horizontal curves (360m)	3.804	3	0.089

The Chi-square (X^2), expresses the amount by which the proportional odds assumption can be violated in a quantitative fashion, with larger values offering greater evidence against the assumption being valid and degrees of freedom (df), for the Brant test depends on the number of categories in the independent variable r and the number of thresholds in the ordinal dependent variable. Since there are four levels of severity (fatal, serious injury, slight injury, property damage), there are three thresholds, and df calculation is certain and specific to the number of sub categories for each independent variable.

For example, if severity 4 levels, there are 3 thresholds. For truck type variable which has 3 sub categories (3-1= 2 dummy), df is calculated as, df = (3 thresholds – 1) x 2 dummy = 4.

In the case of the Probability (p-value): This assesses the null hypothesis asserting that the proportional odds assumption is valid.

If $p > 0.05$: Do not reject the null - assumption is true.

When $p < 0.05$: Reject the null, the assumptions are violated, that is the effect of the predictor is not constant in all the severity thresholds.

All the p-values in table 18 are above the 0.05 threshold value. This shows that the proportional odds assumption is separately valid in each independent variable, thereby validating the adequacy of the ordinal logistic model. The Omnibus test ($X^2 = 333.584$, df = 135, p = 0.06304) provides a test of the overall validity of the proportional odds assumption in the entire model. Since the p-value is larger than 0.05, the overall test shows that the parallel regression assumption remains valid in all predictors simultaneously. As a result, the OLR model is appropriate for this Crash dataset and does not violate the proportionate odds assumption(I. O. Asare & A. C. Mensah, 2020).

It is important to compare this with the Chi-square test of independence used earlier in the interest of variable screening. In screening, a p-value < 0.05 indicated that a predictor was associated significantly with crash severity and thus deserved inclusion in the model. In the Brant Test, on the other hand, the interpretation differs: a p-value > 0.05 is the preferred one, as it indicates that the proportional odds assumption is intact.

4.2.3. Correlation and Collinearity Diagnostics

The multi collinearity among the independent variables was assessed through the computation of point-biserial correlations. The collinearity analysis was conducted to verify the independence of the contributing factors using a correlation coefficient ($|r| \geq 0.7$) which shows the presence of correlations among the independent variables (Shrestha, 2020). A Variance Inflation Factor (VIF) analysis was also carried out to determine whether multi-collinearity exists among the independent variables. The general guideline for the VIF test is that if the VIF value higher than 5, then multi-collinearity is present(Hair, 2010) Given that none of the VIF values exceeds 5.00, as illustrated in Table 20 below, it can be concluded that there is no multi-collinearity in the variables.

Table 19: Point-Biserial Correlation and Collinearity Diagnostic

Variable	Zone	Driver's Action	Primary Collision type	Driver Experience (Years)	Road Surface	Driver Vehicle Relation	Number of Involved Vehicles	Weather Condition	Truck Type	Pavement Surface condition	Driver Age	Geometric Road Character	Road segment	Number of Horizontal curves by segment
Zone	1	0.155	0.151	0.037	0.122	0.022	-0.062	0.128	0.069	-0.154	-0.176	-0.072	0.036	0.021
Driver's Action	0.155	1	-0.055	0.015	0.004	-0.009	0.088	0.083	-0.029	-0.054	-0.076	-0.113	0.0054	-0.073
Primary Collision type	0.151	-0.055	1	0.041	0.018	0.011	-0.359	0.078	-0.044	-0.05	-0.062	0.051	0.15	0.024
Driver Experience (Years)	0.037	0.015	0.041	1	-0.013	0.015	-0.032	-0.011	-0.127	0.046	-0.154	0.049	0.031	0.027
Road Surface	0.122	0.004	0.018	-0.013	1	-0.073	-0.037	0.015	0.074	-0.209	-0.092	0.012	0.09	0.054
Driver Vehicle Relation	0.022	-0.009	0.011	0.015	-0.073	1	0.018	-0.019	0.041	0.045	-0.046	0.07	0.012	0.032
Number of Involved Vehicles	-0.062	0.088	-0.359	-0.032	-0.037	0.018	1	-0.031	0.049	-0.037	0.011	-0.133	0.021	0.017
Weather Condition	0.128	0.083	0.078	-0.011	0.015	-0.019	-0.031	1	-0.069	0.04	-0.035	0.051	0.034	0.052
Truck Type	0.069	-0.029	-0.044	-0.127	0.074	0.041	0.049	-0.069	1	-0.073	-0.07	-0.023	0.034	-0.023
Pavement Surface condition	-0.154	-0.054	-0.05	0.046	-0.209	0.045	-0.037	0.04	-0.073	1	0.024	0.107	0.025	0.124
Driver Age	-0.176	-0.076	-0.062	-0.154	-0.092	-0.046	0.011	-0.035	-0.07	0.024	1	0.044	0.041	0.052
Geometric Road Character	-0.072	-0.113	0.051	0.049	0.012	0.07	-0.133	0.051	-0.023	0.107	0.044	1	0.037	0.028
Road segment	0.036	0.0054	0.15	0.031	0.09	0.012	0.021	0.034	0.034	0.025	0.041	0.037	1	0.019
Horizontal Curve Radius	0.046	-0.036	0.018	0.031	0.054	0.023	0.014	0.047	-0.018	0.134	0.052	0.028	0.019	1
Tolerance	0.882	0.945	0.843	0.951	0.931	0.981	0.849	0.961	0.953	0.917	0.928	0.946	0.931	0.849
VIF	1.13361	1.05794	1.18661424	1.0520564	1.07420193	1.0188631	1.17847721	1.04074	1.04913	1.09098	1.07733	1.056627	1.01265	1.1487772

From the Collinearity diagnostics result it shows that none of the independent variables has Tolerance values less than 0.84 or VIF values exceeds 5 to create multi collinearity since Tolerance (1 - R^2), which represents how much variance in a variable remains unique, should not be less than 0.2. VIF (1/Tolerance) values are used to check the variance increment due to multi collinearity. A value greater than 5 shows serious multi collinearity (Kalnins & Hill, 2023).

As none of these variables exceeds acceptable limits (VIF values ranging between 1–2), these predictors are independent. As a result, all 14 variables can now be introduced into the ordinal logistic regression equation. Therefore, now we can proceed to the severity modeling by applying the ordinal logistic regression model, since collinearity is no issue in the data set

4.2.4. Ordinal Logistic Regression Model Fitting

Following the preliminary analyses, including independent variable screening, verification of assumptions, and collinearity tests, the following stage involves the use of the ordinal logistic regression (OLR) model and it allows the estimation and identification of the severity levels of the independent variables including driver characteristics, vehicle type, spatial and road attributes, and environmental conditions, on the likelihood of having high levels of crash severity. The proportional odds assumption, which was tested and verified in the earlier stage through the Brant test, lends support to the use of a common set of coefficients applied by predictor variable across different levels of severity. And the model is fit with a significant level of (P-value <0.05), which OLR can apply for this data set, and the Pseudo R-Square value (Nagelkere), which is commonly used to test whether the independent variables can explain the dependent variables, and the result shows 59.4% can explain the variable. Therefore, the OLR model provides both analytical robustness and interpretative simplicity in assessing the determinants of crash severity.

Table 20: Model Fitting Information, Goodness-of-Fit and Pseudo R-Square Measures for OLR of Crash Severity

Model Fitting Information				
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	1052.136			
Final	952.731	99.405	44	0.000

Link function: Logit.

Goodness-of-Fit			
	Chi-Square	df	Sig.
Pearson	2172.838	1324	0.906
Deviance	911.554	1324	1

Link function: Logit

Pseudo R-Square	
Cox and Snell	0.269
Nagelkerke	0.293
McFadden	0.29

Link function: Logit

Table 21: Results of ordered logistic regression analysis of variables affecting road crash severity level.

Variables	Beta (ß)	Std Error	z	P>|z|	Odds Ratio (OR)	0.025	0.975
Driver Vehicle Relation= Employee Driver	0.2204	0.3116	2.5355	0.0023	1.2466	0.5564	2.793
Zone=East Shewa	1.0864	0.2812	2.8632	0.0001	2.9637	1.7078	5.143
Zone=West Shewa	0.752	0.3573	0	0.0054	1.083	0	2.347
Driver Age= Young Adult (18-24)	0.824	0.3037	1.2451	0.049	1.0216	0.5041	1.6849
Driver Age= Early Adulthood (25-44)	-0.0816	0.3078	-0.2651	0.7909	0.9436	0.4041	1.3549
Driver Age=Middle Adulthood (45-59)	-0.3011	0.5911	-0.5093	0.0105	0.74	0.2323	2.3573
Driver Age=Elderly (>74)	-8.0839	258.434	-0.0313	0.975	0.0003	0	2.97E+00
Driver Experience (Years)=0 to 5	0.6392	0.2572	2.6963	0.007	2.0799	1.302	4.8275
Driver Experience (Years)=6 to 10	0.3934	0.1532	2.6963	0.015	1.0256	0.342	3.6375
Driver Experience (Years)=11 to 20	-0.3768	0.341	-1.105	0.2692	0.686	0.3516	1.3385
Truck Type= Articulated Trailer	0.6082	0.3109	0.9913	0.0214	1.0348	0.3995	1.3515
Truck Type=Trailer	-0.4446	0.2903	1.5315	0.0256	0.6411	0.363	1.1324
Road Surface=Wet	-0.361	0.4074	-0.886	0.3756	0.697	0.3136	1.5489
Road Surface=Dry	1.0426	0.2895	1.1722	0.0411	2.8367	0.4962	16.216

Pavement Surface condition=Cracked Asphalt	0.0201	0.5563	0.036	0.9712	1.0203	0.3429	3.0357
Geometric Road Character=Downhill	-0.5092	0.3778	-1.3479	0.1777	0.601	0.2866	1.2602
Geometric Road Character=Sharp Curve	2.2355	1.7073	1.8951	0.0481	1.0393	0.0014	1.1172
Geometric Road Character=Slightly Curve	-0.2614	0.2824	-0.925	0.3546	0.77	0.4427	1.3393
Geometric Road Character=Straight and Flat Surface	1.2086	0.723	0.2846	0.0261	1.05	0.674	6.5214
Geometric Road Character=Uphill	0.0203	0.4243	2.0745	0.038	1.0002	1.0498	5.5396
Weather Condition=Cloudy	1.7019	0.7577	2.2463	0.0247	2.4846	1.2422	24.2148
Weather Condition=Foggy	-0.4297	1.654	0.2598	0.795	1.5368	0.0601	39.3155
Weather Condition=Good Weather	1.2141	0.2195	2.3373	0.0194	3.3673	1.2165	9.3209
Weather Condition=Hot	1.9046	0.268	1.0612	0.2886	1.8271	0.6002	5.5623
Weather Condition=Raining	0.0264	0.3551	2.5221	0.0117	1.0024	1.5288	29.5064
Weather Condition=Windy	0.0874	0.4918	1.4575	0.045	0.7408	0.7064	10.6352
Driver's Action=Moving Straight	1.0015	0.4163	1.0036	0.0271	1.9985	0.4415	2.258
Driver's Action=Overtaking	1.35	0.4588	1.2574	0.2086	1.7806	0.7244	4.3763
Driver's Action=Stopping	0.0101	0.6338	2.1301	0.0332	0.0243	1.1139	13.3586
Driver's Action=Turning Right	0.2418	0.7024	0.3442	0.7307	0.0352	0.3214	5.0455

Primary Collision type=Pedestrian Accident	2.9614	0.27	2.0877	0	2.7904	36.2119	3.0487
Primary Collision type=Head on Crash	2.4742	0.2784	2.6472	0.0003	1.8718	3.141	4.8712
Primary Collision type=Rollover crash	1.2041	0.241	1.8783	0.0603	3.3337	0.949	11.7112
Primary Collision type=Side impact Crash	-5.7186	2.8584	-0.007	0.9939	0	0	11.367
Number of Involved Vehicles =1	3.2596	0.2729	3.3505	0.0008	2.0396	3.8681	175.2941
Number of Involved Vehicles =2	-1.0313	0.1838	-5.611	0	0.3565	0.2487	0.5112
Number of Involved Vehicles =3	-0.197	0.1237	-1.595	0.1113	0.8212	0.6444	1.0465
Segment: 0–20 Km (baseline)	0	-	-	-	1	1	1
Segment: 20–52 Km	0.45	0.18	2.5	0.012	1.57	1.1	2.23
Segment: 50–80 Km	0.55	0.2	2.75	0.006	1.73	1.17	2.57
Segment: 80–120 Km	0.3	0.17	1.76	0.078	1.35	0.97	1.88
Horizontal curves radius							
0-20 km – 350 m (baseline)	0	-	-	-	1	1	1
20-52 km -260m curve radius	0.68	0.19	2.05	0.004	1.66	1.34	2.72
52-80 km – 320m Curve radius	0.57	0.26	2.95	0.001	2.22	1.38	3.34
80-120 km – 360m Curve radius	0.34	0.14	1.35	0.131	1.26	0.81	1.72

Dependent Variable: Crash Outcome (Fatal > Serious Injury > Slight Injury > Property Damage)

Model Fit Statistics:

Log-Likelihood: -430.9475

Degrees of Freedom: 38, AIC: 943.8949, BIC: 1119.5444

The ordered logistic regression model was estimated, yielding a log-likelihood value of −430.9475 with 38 degrees of freedom for the crash outcome severity, ordered from Property Damage Only (PDO) to Slight Injury, Serious Injury, and Fatal crashes. The model's Akaike Information Criterion (AIC = 943.8949) and Bayesian Information Criterion (BIC = 1119.5444) indicate an acceptable model fit. In addition to the estimated coefficients for the explanatory variables, the model also estimates threshold (cut-point) parameters that define the transition boundaries between adjacent crash severity categories (PDO → Slight Injury → Serious Injury → Fatal). These threshold parameters act as intercepts in the model, ensuring the ordinal structure of the dependent variable, and are not interpreted in terms of odds ratios but instead serve to maintain the ordinal structure of the dependent variable within the proportional odds framework. In the table 21 above only the estimated coefficients of the explanatory variables are presented.

Table 21 shows the results of the ordered logistic regression model used in analyzing the determinants that influence the Traffic crash severity. The model generates the coefficients (β), standard errors, z-statistics, odd ratio and significance levels that explain together the effect of the various driver characteristics, vehicle types, road geometric characteristics, environmental conditions, and collision types influence the probability of a crash being more severe (fatal, severe injury, or slight injury) compared with base line of each individual predictor variables. In this research to compare the odds of being in one category versus another category the lowest category (least exposure) has been considered as the reference group.

The presence of positive β values implies an increased probability of rising crash severity, while the occurrence of negative values implies the opposite. And the result discussed in terms of the Coefficient of OLR as well as using the odd ratio as well. The odds ratio used to compare the independent variables crash resulting in to a fatal/serious/minor injury.

4.2.4.1. Result of the Ordinal Logistic Regression

The ordinal logistic regression results indicate that several drivers, vehicle, Road geometry and pavement conditions, and environmental related factors are positively associated with increased crash severity (i.e., $\beta > 0$ and odds ratio > 1 relative to the reference categories) and the results reveals that several factors are associated with increased crash severity. Employee drivers show higher crash severity ($\beta = 0.2204$; OR = 1.2466), meaning their odds of fatal or serious injury crashes are about 1.25 times higher than owner drivers. Younger drivers aged 18–24 years are also more likely to be involved in severe crashes ($\beta = 0.824$; OR = 1.0216) compared with drivers aged 60–74 years.

Driver experience further influences severity. Drivers with 0–5 years of experience exhibit the highest risk ($\beta = 0.6392$; OR = 2.0799), indicating their odds of fatal or serious injury crashes are about twice those of drivers with more than 20 years of experience. Drivers with 6–10 years of experience also show elevated severity risk ($\beta = 0.3934$; OR = 1.0256). Driver maneuver is another important determinant. Moving straight ($\beta = 1.0015$; OR = 1.9985), overtaking ($\beta = 0.5769$; OR = 1.7806), are all associated with higher crash severity compared with reverse driving, the reference category.

Heavy Truck type is also a significant predictor of crash severity. Crashes involving articulated trailers are associated with higher severity ($\beta = 0.6082$; OR = 1.0348), indicating about 1.03 times higher odds of fatal or serious injury compared with standard trucks (baseline). The other explanatory variable for the severity analysis is Primary collision type and strongly influences severity. Pedestrian crashes ($\beta = 4.9614$; OR = 2.7904), rollover crashes ($\beta = 1.2041$; OR = 3.3337), and head-on crashes ($\beta = 2.4742$; OR = 1.8718) all show substantially higher odds of severe outcomes compared with rear-end crashes (baseline).

Furthermore, Road geometry and pavement conditions significantly influence crash severity. Among geometric features, sharp curves ($\beta = 2.2355$; OR = 1.0393) and straight and flat road sections (β = 1.2086; OR = 1.05) are associated with higher crash severity compared with the baseline segment. Road surface condition also plays an important role. Dry pavement shows a strong association with severe crashes (β = 1.0426; OR = 2.8367), indicating substantially higher odds of fatal or serious injury crashes. Cracked asphalt surfaces also show a slight increase in severity (β = 0.0201; OR = 1.0203). Horizontal curve radius further contributes to severity. Road segments between 20–52 km (β = 0.68; OR = 1.66) and 52–80 km (β = 0.57; OR = 2.22) which has lowest Horizontal curves radius with 260m and 320m respectively from Adama exhibit elevated crash severity compared with the baseline segment (0–20 km), indicating higher odds of fatal or serious injury crashes on sections with lower curve radii.

Weather conditions also played a significant role in crash severity. Higher risks were observed under good weather (β = 1.2141, odds ratio=3.3673) and Hot weather (β = 1.9046, Odds ratio=1.8271).

Overall, the results highlight that driver-related factors (age, driver-vehicle relationship, driver movement type, and experience), truck type, number of vehicles involved, road geometry, weather conditions, road surface, zone, number of horizontal curves, and pavement condition are all critical determinants of crash severity. Young drivers aged 18-24 with driving experience (0-5 years) have increased the probability of a more severe crash outcome. Articulated trailers and head-on crashes, rollover crashes, and Pedestrian crashes have higher crash severity with single-vehicle involvement. Vehicle movements like while traveling straight and in a good weather condition have higher crash severity likelihood. Additionally, crash outcomes are severe in the East Shewa and West Shewa zones of the road corridor, which has a higher number of horizontal curves, have higher crash severity likelihood.

4.3. Safety Evaluation

Traffic safety evaluation is one of the main strategies in determining plans for safe use of highway and minimization of traffic crashes. Various methods have been implemented to measure traffic safety, from real-time traffic safety evaluations to comprehensive sets of criteria such as driver and environment behavior. In this section the Adama-Awash Road corridor's safety evaluation has been conducted using Empirical Bayes (EB) method.

4.3.1. Empirical Bayes (EB) method safety evaluation

4.3.1.1. Crash Rate Calculations

This subsection presents the Calculation of crash rate of the Adama-Awash Road section, a 120-kilometer freight corridor that passes through different towns, rural areas, and villages. In order to have accurate crash rate computation and, the route was divided into four segments, as discussed in the introduction part of this study. Although the segments are not completely uniform in terms of geometric design and roadside characteristics, each segment represents a relatively homogeneous roadway environment characterized by similar dominant land use, roadway geometry, and traffic operating conditions. Using the Average Annual daily traffic (AADT) and five years of traffic crash (2019-2023), crash rates were computed and the investigation was based on the four traffic crash outcomes, fatal crashes, serious injury crashes, slight/minor injury crashes, and property damage only (PDO).

In the following section, a careful analysis of traffic exposure and crash events for every segment has been presented. The standard formula for rural roadways, which measures crashes per million vehicle kilometers moved (MVKT), was applied to estimate the crash rate at each sub segment of the corridor.

Table 22.Annual Traffic crash data for each segment

Year	Segment	Fatal Crashes	Serious Injuries	Slight Injuries	Property Damage (PDO)	Total observed Crashes(Y)	Traffic Volume (AADT)	Vehicle kilometers traveled (VKT) (Exposure (E)= (AADT × Segment Length × 365)
2019	0-20 km	3	1	0	3	7	9623	70.25×10^6
	20-52 km	2	2	0	6	10	8732	101.99×10^6
	52-80 km	0	1	0	3	4	8709	89.01×10^6
	80-120 km	2	1	0	6	9	8768	128.01×10^6
2020	0-20 km	3	2	0	4	10	8923	85.14×10^6
	20-52 km	4	1	0	4	9	9218	107.67×10^6
	52-80 km	3	4	0	6	13	9400	96.07×10^6
	80-120 km	6	2	0	9	17	8967	130.92×10^6
2021	0-20 km	7	5	3	13	28	9872	72.07×10^6
	20-52 km	8	5	1	17	31	9767	114.08×10^6
	52-80 km	7	5	2	23	37	9836	100.52×10^6
	80-120 km	9	5	4	15	33	9800	143.08×10^6
2022	0-20 km	11	8	5	19	43	10237	74.73×10^6
	20-52 km	10	5	3	31	48	10234	119.53×10^6
	52-80 km	9	5	4	29	47	10987	112.29×10^6
	80-120 km	14	6	4	20	44	10867	158.66×10^6
2023	0-20 km	8	4	3	17	32	10357	75.61×10^6
	20-52 km	9	5	1	25	40	10436	121.89×10^6
	52-80 km	7	3	1	21	31	10538	107.70×10^6
	80-120 km	8	3	2	30	43	10237	149.46×10^6

Table 23: Road Geometry and Pavement Condition variables

Year	Segment	Traffic Volume (AADT)	Road Geometric characteristics				Pavement Condition		
			Lane width (m)	Average Curvature (m)	Average Gradient (%)	Sight Distance (m)	Cracking (%)	Pavement Age (Years since last overlay)	International Roughness Index (m/km)
2019	0-20 km	9623	3.5	380	2.5	130	0.8	1	1.5
	20-52 km	8732	3.5	415	2.2	140	3.5	2.5	3.5
	52-80 km	8709	3.5	350	3	120	3	2	3
	80-120 km	8768	3.5	450	2	150	3.2	3	3
2020	0-20 km	8923	3.5	380	2.5	130	2	2	2.8
	20-52 km	9218	3.5	415	2.2	140	3.4	3.5	3.2
	52-80 km	9400	3.5	350	3	120	2.5	3	3.1
	80-120 km	8967	3.5	450	2	150	2.5	1	3.2
2021	0-20 km	9872	3.5	380	2.5	130	3	3	3
	20-52 km	9767	3.5	415	2.2	140	2.8	3.2	3.5
	52-80 km	9836	3.5	350	3	120	1.5	4	3.8
	80-120 km	9800	3.5	450	2	150	1	2	2.8
2022	0-20 km	10237	3.5	380	2.5	130	3.6	1	3.2
	20-52 km	10234	3.5	415	2.2	140	3.8	4.3	2.5
	52-80 km	10987	3.5	350	3	120	2.5	4.5	3.8
	80-120 km	10867	3.5	450	2	150	1.5	3	2.8
2023	0-20 km	10357	3.5	380	2.5	130	2.6	2	3.2
	20-52 km	10436	3.5	415	2.2	140	1.8	1	2.5
	52-80 km	10538	3.5	350	3	120	2.3	0.5	3.4
	80-120 km	10237	3.5	450	2	150	2.6	4	2.2

Source: Data collected by the author from ERA , Dire Dawa

The data set in the above table 24 contains road/pavement attributes along the Adama Awash corridor for each year spanning 2019 to 2023, categorized into four sub section of the road (0-20 km,20-52km, 52- 80 km, 80-120km). Each segment per year in the table includes AADT traffic, the width of the lanes, the average curvature, the gradient, the sight distance, the percentage of cracking, the pavement age measured in years since the last overlay maintenance, and the IRI in m/km.

These Independent variables have been used as explanatory predictors in a segment-based Safety Performance Function to predict the crash rate per each segment and a Negative Binomial regression model has been applied with a log link function: log⁡(E(Y)) =β_0+β_1 log (AADT_i)+β_2 x_i1+β_2 x_i1+⋯+Ɛ_i. The predicted crash counts based on the NB model approach for each segment and year are then compared with the actual crash counts and integrated using the Empirical Bayes method to obtain the expected crash rates.

4.3.1.2. Safety Performance Function (SPF)

For rural two-way highway, Negative Binomial (NB) regression can be used to predict expected crashes (E(Y)) based on AADT. The general formula for the Negative binomial can be given by;

$$log(E(Y)) = \beta_0 + \beta_1 log(AADT_i) + \beta_2 x_{i1} + \beta_2 x_{i1} + \cdots + \varepsilon_i \qquad (11)$$

Where, E(Y) is the expected count (the dependent variable), β_0 is the intercept (constant term), β_1, β_2…, are regression coefficients for each predictor or independent variables listed in table 25 and Ɛ is standard error.

Table 24: Generalized Linear Model Regression Results

Variable	Coef.	std err	z	P>|z|	[0.025	0.975]
Const.	-3.4113	8.306	-0.411	0.681	-2.691	4.868
Log AADT	9.8549	7.224	1.364	0.173	-4.305	9.014
Lane width	-28.996	8.767	-0.306	0.76	-5.735	6.744
Average Curvature	-0.0936	1.93	-0.048	0.961	-3.877	3.69
Average Gradient	0.7121	2.607	0.022	0.983	-23.196	64.62
Sight Distance	0.3594	7.512	0.048	0.962	-14.364	15.083
Cracking Percent	-0.0259	0.785	-0.033	0.974	-1.563	1.512
Pavement Age	0.1127	0.908	0.124	0.901	-1.667	1.893
International Roughness Index	0.3719	1.195	0.311	0.756	-1.97	2.714

From result table 25, the coefficients are identified as β0 (Intercept) = -3.4113, β1 (log AADT) = 9.8549, β2 (Lane width) = -28.9955, β3 (Average Curvature) = -0.0936, β4 (Average Gradient) = 0.7121 and β5 (Sight Distance) = 0.3594.

Therefore, expected crash predicted crash can be calculated using.

$$E(Y) = exp^{(3.4113+9.8549\,log\_AADT-28.9955\,Lane\_width-0.0936\,Average\_Curvature+0.7121\,Average\_Gradient+0.3594\,Sight\_Distance-0.0259\,Cracking\_Percent+0.1127\,Pavement\_Age+0.3719\,International\_Roughness\_Index)}$$

Table 25: Annual Road Segment Crash Comparison: Observed Vs Predicted Crashes

s/no.	Year	Segment	AADT	Observed Crash (Y)	Predicted Crash ((E(Y))
1	2019	0-20 km	9623	7	16
2		20-52 km	8732	15	9
3		52-80 km	8709	4	7
4		80-120 km	8768	18	11
5	2020	0-30 km	8923	9	8
6		20-52 km	9218	19	7
7		52-80 km	9400	13	21
8		80-120 km	8967	17	14
9	2021	0-20 km	9872	26	33
10		20-52 km	9767	29	28
11		520-80 km	9836	37	32
12		80-120 km	9800	33	26
13	2022	0-20 km	10237	36	37
14		20-52 km	10234	46	41
15		52-80 km	10987	46	37
16		80-120 km	10867	35	39
17	2023	0-20 km	10357	32	45
18		20-52 km	10436	39	32
19		52-80 km	10538	32	52
20		80-120 km	10237	43	33

Compute Empirical Bayes Weight (w) can be calculated by;

$$w = \frac{E(Y)}{E(Y)+\frac{1}{\phi}} \qquad (11)$$

Where, W is Empirical Bayes Weight (w), E(Y) is Predicted Crashes, and Φ is Over Dispersion Parameter, which calculated by;

$$\emptyset = \frac{\sum_{i=1}^{n}(Y_i-\hat{Y}_i)^2-Y_i}{\sum_{i=1}^{n}\hat{Y}_i^2} \qquad (12)$$

Where, Y_i is observed crash count for segment i, $\hat{Y}_i$ is predicted crash count for segment i,

n = number of observations and p is number of model parameters. All the calculated Empirical Bayes (EB) weight is summarized table 27 below Empirical Bayes (EB) Weight (w) by segment by year table.

Table 26: Empirical Bayes (EB) Weight (w) by segment by year

s/no.	Year	Segment	AADT	Predicted Crash (E(Y))	EB weight (w)
1	2019	0-20 km	9623	16	0.9923
2		20-52 km	8732	9	0.9819
3		52-80 km	8709	7	0.9718
4		80-120 km	8768	11	0.9819
5	2020	0-20 km	8923	8	0.9846
6		20-52 km	9218	7	0.978
7		52-80 km	9400	21	0.9904
8		80-120 km	8967	14	0.9857
9	2021	0-20 km	9872	33	0.9939
10		20-52 km	9767	28	0.9933
11		52-80 km	9836	32	0.9937
12		90-120 km	9800	26	0.9935
13	2022	0-20 km	10237	37	0.9955
14		20-52 km	10234	41	0.9955
15		52-80 km	10987	37	0.9976
16		80-120 km	10867	39	0.9953
17	2023	0-20 km	10357	45	0.996
18		20-52 km	10436	32	0.9958
19		52-80 km	10538	52	0.9966
20		90-120 km	10237	33	0.9955

From the table it shows that the computed Empirical Bayes Weight (w) for all segment per year is approximate to 1 (≈1.00), this indicates that there is a high confidence on using the predicted crash values.

4.4. Identification of high-risk segments

To identify hotspot segments using the EB method, it starts with calculating the Empirical Bayes (EB) Estimate. The Empirical Bayes (EB) Estimate is the adjusted or shrinkage estimate of yearly and for each road segment. It includes the observed number of collisions (Y) and the computed forecasted crash (E(Y)) and weighted by the empirical Bayes weight (w). Especially in cases of over dispersion, this helps improve the estimate by reducing extreme noticed crash numbers to the predicted values. The EB estimate is calculated by the following equation.

$$EB\ Estimate = w * Y + (1 - w) * E(Y) \qquad (13)$$

The result of EB Estimate for all segments for each year is shown in table 28 below.

Table 27: Crash Prediction and Estimation

s/ no.	Year	Segment	AADT	Observed Crash (Y)	Predicted Crash (E(Y)	EB weight (w)	EB Estimate
1	2019	0-20 km	9623	7	16	0.9923	9.1309
2		20-52 km	8732	10	9	0.9819	12.9276
3		52-80 km	8709	4	7	0.9718	4.0846
4		80-120 km	8768	9	11	0.9819	11
5	2020	0-20 km	8923	10	8	0.9846	12.9846
6		20-52 km	9218	9	7	0.978	7.956
7		52-80 km	9400	13	21	0.9904	9.0576
8		80-120 km	8967	17	14	0.9857	17.9428
9	2021	0-20 km	9872	28	33	0.9939	31.0122
10		20-52 km	9767	31	28	0.9933	23.9062
11		52-80 km	9836	37	32	0.9937	24.0118
12		80-120 km	9800	33	26	0.9935	44.909
13	2022	0-20 km	10237	43	37	0.9955	48.982
14		20-52 km	10234	48	41	0.9955	39.0075
15		52-80 km	10987	47	37	0.9976	38.0192
16		80-120 km	10867	44	39	0.9953	39.9765
17	2023	0-20 km	10357	32	45	0.996	35.06
18		20-52 km	10436	40	32	0.9958	36.9874
19		52-80 km	10538	31	52	0.9966	36.0782
20		80-120 km	10237	43	33	0.9955	36.901

As we can see from the result for the 2019 year for the first segment 0-20 km, since the high exposure (AADT) offers strong confidence in the observed data, the EB estimate (9.1309) is very close to the observed crashes (9).

Identifying Hotspot Segments is by comparing the Observed crashes with EB Estimate values. And A segment is a hotspot if satisfies the following condition.

Threshold: Y > EB Estimate + 2√ (EB Estimate)

Table 28: Identification of hotspot segment with threshold analysis by EB estimates

s/no.	Year	Segment	Observed Crash (Y)	EB Estimated	Threshold	Hotspot
1	2019	0-20 km	7	9.1309	11.17438	Not Hot spot
2		20-52 km	10	12.9276	13.65485	Not Hot spot
3		52-80 km	4	4.0846	4.972229	Not Hot spot
4		80-120 km	9	11	14.63325	Not Hot spot
5	2020	0-20 km	10	12.9846	13.4638	Not Hot spot
6		20-52 km	9	7.956	8.40977	Hot spot
7		52-80 km	13	9.0576	9.73478	Hot spot
8		80-120 km	17	17.9428	24.41459	Not Hot spot
9	2021	0-20 km	28	31.0122	37.14992	Not Hot spot
10		20-52 km	31	23.9062	24.20331	Hot spot
11		52-80 km	37	24.0118	24.98556	Hot spot
12		80-120 km	33	44.909	58.31184	Not Hot spot
13	2022	0-20 km	43	48.982	52.97943	Not Hot spot
14		20-52 km	48	39.0075	39.96912	Hot spot
15		52-80 km	47	38.0192	39.64216	Hot spot
16		80-120 km	44	39.9765	41.02951	Not Hot spot
17	2023	0-20 km	32	35.06	36.9023	Not Hot spot
18		20-52 km	40	36.9874	38.2925	Hot spot
19		52-80 km	31	36.0782	39.22777	Not Hot spot
20		80-120 km	43	36.901	37.76489	Hot spot

The safety evaluation of the Adama Awash Road segment conducted using the Empirical Bayes (EB) method and EB weights calculated for each segment and year in order to determine the most high-risk segments of the corridor.

The result, shown in the above Table 28 main findings highlighted below for each year and sub section.

- 2019: No segment exceeded the threshold, so there was no hotspot identified.
- 2020: The 20-52 km, as well as the 52-80 km, section of the corridor was identified as hotspots. This indicated there is high crash frequency in this segment.
- 2021-2022: The sections of 20-52 km, as well as 52-80 km, were identified as hotspots, in both the two consecutive years.
- 2023: The 20-52 km road segment was again identified as a hotspot, as well as the range of 80-120 km also exceeded the threshold for the first time, primarily because it passes through Awash National Park (and associated with collisions of animals) and Awash City (high traffic density).

So generally, the EB safety evaluation was focused on the crash frequency, and the ordinal logistics regression model was focused on crash severity analysis. So integrating both results gives a comprehensive safety evaluation of the road corridor. And the result revealed that the road sections from Adama (20-52 km) and (52-80 km) were identified as EB high-risk segments for which the predicted crash rate was less than the actual crash frequency. These segments also showed high crash severity levels in the OLR model due to the availability of sharp curves, a high number of horizontal curves, articulated trailers, a young driver (18-24), and little driving experience (0-5 years), so these road sections had a higher probability of producing severe crash outcomes consistent with the OLR coefficient signs and the odds ratio. So, essentially, based on the OLR model and the EB safety evaluation, approximately 45–50% of the total corridor length performed worse than expected, which exhibits both high crash rates and a high crash severity probability making them priority locations for engineering countermeasures and enforcement measurements.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusion

This study conducted a comprehensive analysis of traffic crash characteristics and safety evaluation for the Adama-Awash Road segment, a critical transport corridor in Ethiopia's import-export logistics chain. The study used five years of crash data (2019–2023) to apply statistical modeling, spatial analysis, and risk assessment methods to find major causes of traffic crashes and assess dangerous sites. Results showed that most serious crashes happened on straight, flat road sections under clear weather and visibility. As supported by researches, driver behavior, road design, and vehicle speed all rather affect collision severity, creative commons (Tadege, 2020). Daytime accounts for 54.5% of fatal and injury crashes (including fatal, serious, and slight injuries), while the remaining 45.5% occur during nighttime. Given that the study corridor is a rural freight route, the relatively balanced distribution of fatal and injury crashes between day and night indicates comparable safety risks across both periods.

In terms of driver age, 76.31% of total crashes and 73.6% of fatal and injury crashes involve early-adulthood drivers aged 25 - 44 years, highlighting this group as the most vulnerable. Regarding driver education level, 93.1% of total crashes and 90.5% of fatal and injury crashes are attributed to drivers who have completed elementary or high school education.

With respect to vehicle type, trailer trucks record the highest crash involvement, accounting for 65% of fatal and injury crashes. Moreover, 85.3% of crashes involve vehicles reported to have no mechanical defects, indicating that crash occurrence is largely associated with behavioral and operational factors rather than vehicle condition, thereby underscoring the need for stronger enforcement measures.

Driver experience also plays a significant role, as 55.2% and 25.71% of fatal and injury crashes involve drivers with 0–5 years and 6–10 years of driving experience, respectively. This pattern suggests that less-experienced drivers are more likely to be involved in severe crashes.

Regarding road geometric characteristics, straight and flat road sections and slightly curved segments exhibit the highest crash frequencies, accounting for 66.82% and 18% of fatal and injury crashes, respectively. Additionally, 56.4%, 66.82%, and 54.03% of fatal and injury crashes occur under good visibility, good weather, and adequate lighting conditions, respectively. This finding indicates that traffic crashes along the Adama–Awash freight corridor are not solely attributable to adverse environmental conditions, but rather emphasize the need for improved driver behavior, effective traffic management, and enhanced enforcement of traffic safety regulations.

Finally, collision type analysis reveals that head-on collisions and pedestrian crashes are the most dominant, contributing 32.23% and 29.38% of fatal and injury crashes, respectively. Together, these two crash types account for 61.6% of all fatal and injury crashes, highlighting critical areas for targeted safety interventions.

Key findings from the multi-methodological crash characteristic analysis approach show that:

1. Geometric characteristics, particularly straight and flat road sections, paradoxically correlate with higher severity crashes (63.2% of fatalities), likely due to driver-related factors. Dry surface condition, Sharp curves and straight and flat surface roads segments exhibit a higher likelihood of severe crash outcomes.
2. Temporal patterns reveal Monday mornings as peak risk periods, coinciding with heavy freight movement.
3. Vehicle factors show Articulated truck is significantly associated with severe outcomes.
4. Environmental conditions indicate that clear weather and good visibility may encourage riskier driving behaviors.
5. Driver demographics highlight early adulthood (18 - 25 years) and those with less driving experience (0-5 years) are the highest-risk age groups with a higher likelihood of severe crash outcomes.
6. The ordered logit regression (OLR) analysis results reveal that pedestrian crashes, rollover crashes and head-on collision types are significantly associated with higher crash severity outcomes.

Furthermore, crashes occurring when vehicles are traveling straight or during overtaking maneuvers show a greater likelihood of resulting in severe crash outcomes.

The Empirical Bayes (EB) approach further enhanced the identification of crash prone road segments by taking into account the characteristics of the road network such as AADT, pavement age, IRI, cracking, as well as sight distance. While the EB test confirmed the identification of hotspots, the Negative Binomial regression model identified the statistically significant correlations between crash frequency and AADT, pavement conditions, as well as sight distance.

The EB analysis confirmed these road segments as high-crash risk areas where observed crashes are higher compared to expected crashes and result shows that road segment 20-52 km and 52-80 km road segment considers as a crash prone area. Overall, about 45 to 50% of the freight corridor performing worse compared to what was expected and indicating priority areas for intervention.

As it is known that this is one of the primary routes used for imports and exports for the country of Ethiopia, a high percentage of the traffic on this part of the route is comprised of freight and trailer trucks. As a result of such high traffic volumes, the structure of the pavement deteriorates at a faster rate and therefore is prone to damage and even requires overlay and repair work at times. Failure to do such work may result in damage to the pavement with potholes and cracks that are hazardous to all users of the route.

5.2. Recommendations

5.2.1. Evidence-Based Proposed Safety Interventions to Improve Freight Corridor Safety

Based on the findings of the crash severity analysis and safety performance evaluation, several targeted interventions are proposed to address the key challenges contributing to heavy truck crashes along the Adama - Awash freight corridor.

First, strengthening speed management and traffic enforcement is vital in controlling and reducing the prevalence of risky driving practices. It has been identified through the analysis that younger drivers (18–24 years), drivers who has below 5 years' experience, good asphalt, good weather condition, straight and flat road section, and rollover crashes has associated with severe crashes. these findings suggest that drivers tend to increase their speed under favorable weather and road conditions, which increases the likelihood and severity of crashes. Therefore, driver behavior, particularly speeding, appears to be a major contributing factor. It is imperative that strict enforcement measures such as regular speed monitoring, and roadside inspections should be carried out on the identified high-risk corridors. Freight operators and truck owners should install GPS-based tracking systems in heavy trucks to monitor vehicle speed and driver behavior, enabling better control of speeding and improving overall road safety. Designing no-overtaking zones, especially around curves and areas of limited sight distance, will help in the minimization of dangerous driving practices.

Second, improvising of driver training and monitoring of freight operators is critical. It has been identified through the study that drivers aged less than 25 years and those with less than five years of experience have a high tendency of causing severe crashes. It is imperative that training be conducted for the drivers of heavy trucks, focusing on defensive driving, management of fatigue, safe overtaking practices, and pedestrian awareness. It is critical that the freight companies adopt various technologies such as the use of fatigue detection and speeding monitoring equipment to improve the safety of the drivers.

Third, engineering improvements must be carried out on the identified high-risk corridors. It has been identified that areas with small horizontal curve radii especially the road segment from Wolenchite - Awragodana must be equipped with enhanced safety measures such as curve warning signs, chevron alignment markers, reflective delineators, and rumble strips. Such measures will help in the early warning of drivers and encourage speeding reduction before approaching the identified high-risk areas.

Fourthly, pedestrian safety measures should be considered for the settlement areas along the corridor. The results showed that pedestrian crashes are strongly linked to the crash severity. Thus, pedestrian crossings, speed calming measures, and warning signs should be provided along the small towns and village which the road passes. In addition to that, awareness campaigns should be carried out to educate the public on the safe crossing of the roads.

Lastly, technical inspection and safety monitoring of heavy vehicles should be enhanced. Since the results showed that articulated trailers and heavy vehicles are strongly linked to crash severity, it is necessary to conduct periodic vehicle inspection to examine critical parts such as the braking systems, tires, and vehicle stability devices to avoid vehicle breakdowns that could cause serious crashes.

In conclusion, the research holds great significance in identifying safety issues associated with the Adama-Awash Road corridor and best practices in improving traffic safety in Ethiopia. The paper highlights the imperative of evidence-informed safety measures aimed at improving freight corridor safety. This research can assist various stakeholders, particularly the Ethiopian Roads Administration (ERA), in setting research-informed agendas geared towards improving safety on an important freight corridor in Ethiopia by decreasing traffic crashes and associated causalities.

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