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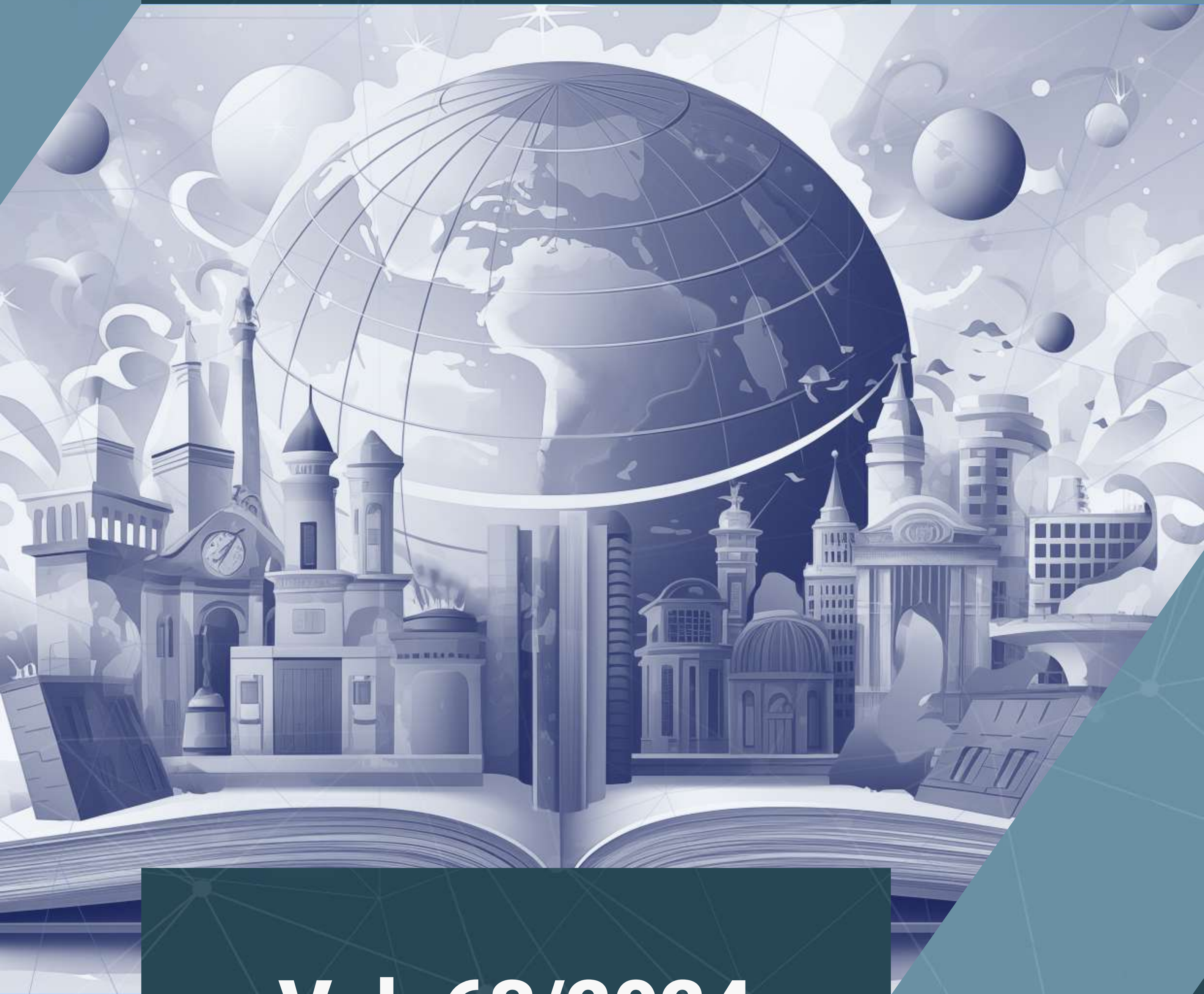

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When does Reckless Driving Occurs? Case Study in Nampula, Mozambique

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Abstract. This study investigates the influence of traffic conditions on reckless driving behavior in Nampula, Mozambique, where road accidents claim several lives daily. Previous research has largely focused on individual driving behaviors, neglecting the impact of traffic environments on such behaviors. This study addresses this gap by categorizing vehicles into four groups: passenger cars, minibuses, trucks, and motorcycles, and classifying traffic conditions using k-means clustering. Three distinct traffic patterns were identified: Motorcycle and Car Dominant Traffic (MCDT), High-Density Traffic Flow (HDTf), and Low-Density Traffic Flow (LDTf). Results show that reckless driving is significantly influenced by traffic conditions, with minibuses, motorcycles, and trucks being key contributors. Pattern 2 (HDTf) demonstrated the highest occurrence of reckless driving, driven by competition among minibus drivers, the obstructive presence of trucks, and risky motorcycle maneuvers. Pattern 1 also exhibited elevated risk, particularly performed among motorcycle riders, while Pattern 3 (LDTf) showed the lowest risk due to reduced traffic density. Poisson regression analysis revealed that increased traffic flow in any vehicle category is associated with higher rates of reckless driving. Minibuses and motorcycles, functioning as demand-oriented public transport, engage in competitive and unsafe behaviors, while trucks, though not engaging in reckless driving directly, act as barriers that exacerbate risky maneuvers by other vehicles. These findings highlight the need for dedicated lanes for minibuses and motorcycles and tailored traffic safety policies to mitigate reckless driving.

Keywords. Reckless driving, Traffic condition, K-means clustering, public transport, Poisson regression

1. Introduction

1.1 Introduce the Problem

Globally, road accidents claim a substantial number of lives daily. According to the World Health Organization (WHO), an estimated 1.19 million people died due to road traffic incidents in 2021, equating to 15 deaths per 100,000 people (Bloomberg 2023). Alarmingly, 90% of these fatalities occur in low- and middle-income countries, particularly in Africa, where motorcycle-related deaths account for 28% of the total (Gulisano and Bella 2021). Despite having a relatively small share of the world's vehicles, these regions suffer disproportionately from road traffic fatalities. This disparity is exacerbated by the ineffectiveness of traffic safety policies and the near absence of robust traffic monitoring systems, leading to widespread non-compliance with safety measures by both drivers and motorcycle riders (Miyajima and Takeda 2007; Walugembe et al. 2020)

Driver behaviour is shaped by a range of factors, including individual driving styles, experiences, and emotions which manifest in diverse driving habits, among them reckless driving is particularly concerning. Reckless driving encompasses a broad spectrum of dangerous driving behaviours that significantly increase the risk of severe accidents (Alkinani, Khan, and Arshad 2020). Reckless driving behaviour is widely recognized as a critical determinant of road safety (Wouters and Bos 2000; Jaroszweski and Mcnamara 2014; Bella 2011; Li et al. 2015; Jovic et al. 2018). Studies have consistently linked certain driving manoeuvres—such as lane changes, overtaking, abrupt braking, and reckless vehicle operation—to a higher risk of road traffic crashes (Ali et al. 2019; Shah and Lee 2021; Abdulhafedh 2017; Vinish et al. 2023; (Xiao 2020) according to Niu,et al (2021), 95% of crashes are associated with human factors, where else 90% are caused by the unsafe driving behaviours. Although a great number of literatures have attempted to explore the factors interfering with driver behaviour, most of them have been focused on the objective factors such as individual human behaviours, age, gender, level of education and other socio-demographic factors (Chebat et al. 2021; Lastrucci et al. 2021; Shirmohammadi, Hadadi, and Saeedian 2019). However, few studies have paid attention to the effect of the road traffic enviroument on the driving behaviors (Yasir Ali et al. 2020; Niu, Li, and Fan 2021; Singh and Kathuria 2021; Xu, Guo, and Sun 2022). It is, therefore, crutial to understand the effect of the traffic enviorounment on the driver/riders behavior, specialy when the mixed traffic is observed.

Problem statement

The increasing incidence of road accidents within Nampula's urban network has become a significant concern, particularly involving motorcycles and minibuses used for public transport. In the city of Nampula, it is widely believed that reckless driving behaviors are the primary cause of these accidents, a belief supported by frequent observations of minibus drivers and motorcycle riders disregarding traffic safety measures.

This study is premised on the assumption that as motorcycles and minibuses operate as demand-oriented public transport, the increased supply of these services leads to inevitable competition among them. This competition drives both drivers and riders to ignore safety protocols, resulting in reckless and aggressive driving behaviors. Given the mixed traffic conditions which characterize the traffic stream in the city of Nampula, this study aims to understand how the traffic environment composition, traffic stream, contributes to the reckless driving behaviors.

2. Method

The study area

The data were collected in two segments of approximately 100 meters length each along the National Road (EN1) in Nampula, namely Muako-wanvela and Nampako.

Muako-wanvela is distinguished as a permanent roadside marketplace, predominantly occupied by informal vendors, with some fixed kiosks as well. It serves as a stopping point for minibuses to embark and disembark passengers. Although the road was originally designed to have one lane for each direction, the persistent presence of street vendors, consumers, and commuters contributes to overcrowding, resulting in a reduced road capacity. Muako-wanvela serves as an access point to two minibuses terminals, Substação and

Marrere. The road surface leading to Marrere terminal, where is located one of the two major hospitals of the city and a well know university in the region, is in suboptimal condition, contributing to the reduction in the number minibuses' traffic towards this terminal, however, increasing the number of motorcycle taxis.

In contrast, Nampako represents a straight-line road segment along the EN1 with one lane for each direction. The road surface is well-maintained, and no specific activities are conducted along the roadside. However, like Muako-wanvela, Nampako segment leads to a new residential area.

For both sites, the data were collected on a segment length of 100 meters.

Figure 1
Muako-wanvela

Figure 2
Nampako

Data Collection

In both road segments, Muako-wanvela and Nampako, traffic flow data were systematically gathered; vehicles classification was conducted based on their dimensions and activities, resulting in the identification of five categories: i) motorcycles, ii) particular cars, iii) minibuses (limited to those operating as public transport, locally known as "chapa"), and iv) trucks (vehicles with a weight exceeding 4,000 tons). At each 5-minute time interval, the traffic flow of each vehicle category was recorded separately, specifying the trajectory as either "in" or "out," indicating movement toward or away from the city Centre, respectively. Simultaneously, during the same time intervals, the occurrence of hazardous manoeuvres in the traffic flow was counted. In this study, a hazard manoeuvre represent any of the following:

abrupt lane changes, sudden turns, zigzag driving behaviour, overtaking on the left side or simultaneously on both sides, and sudden braking; in total for both sites 160 events were recorded. Data collection spanned from 6:00 AM to 12:00 PM over five days, from February 1st to 5th, 2022. A total of 1209 collected samples were obtained

Data cleaning

Since data were collected in 5-minute intervals, only hours with at least 10 (ten) time units, out of 12 (twelve) units in total, were considered. This leads to a total of 1081 samples with 102 reckless driving events observed.

Distribution of the vehicles' categories at the sites

The Table 1 shows the average and the deviation of the traffic flow of each vehicle category, for both sites.

Table 1
Penetration level of vehicles category at the sites

Vehicle categories	n (%)	Muako-wanvela (μ, σ)	Nampako (μ, σ)
Minibuses "Chapa"	8.827 (20.8%)	(6, 2)	(9, 3)
Motorcycles taxi	18.260 (43.1%)	(22, 6)	(14, 5)
Particular Cars	13.866 (32.7%)	(14, 4)	(12, 5)
Trucks	1.399 (3.30%)	(4, 2)	(5, 2)
Total Vehicles	42.352 (100%)	(46, 9)	(42, 9)

Data Analysis

Four distinct analytical steps were employed to examine the influence of traffic conditions on reckless driving behavior.

Cluster of the traffic flow – to identify the existing traffic patterns (first step)

Cluster analysis, an unsupervised method, was employed to identify inherent patterns within the traffic stream. Traffic flow data for different vehicle categories (particular cars, minibuses, trucks, and motorcycles) served as the primary clustering factors. To avoid overshadowing the key variables, categorical factors such as traffic direction (inbound and outbound) and data collection locations (Muako-Wanvela and Nampako) were deliberately excluded, as these could potentially function as "swamping variables".

The K-means clustering method was applied, and the optimal number of clusters was determined using the elbow method. This approach identifies the point where adding more clusters no longer significantly reduces the within-cluster sum of squares (WCSS). Assuming traffic patterns from the cluster analysis are independent, the Kolmogorov-Smirnov test was used to check if the dependent variable—the number of reckless manoeuvres—follows a normal distribution. The Mann-Whitney U test was then applied to assess differences in reckless manoeuvres between traffic patterns.

Driving exposure determination (second step)

Exposure is crucial for assessing the extent of reckless driving across various traffic situations, allowing comparisons that cannot be made using absolute frequency counts (Ryder et al. 2018). However, such comparisons require a common measure of exposure. In this study, each traffic pattern defines the conditions under which reckless driving behaviours are estimated. Exposure is calculated based on the time spent in each traffic pattern or condition, expressed as vehicle's hours travelled (VHT). Since each traffic pattern involves different vehicle categories, all vehicles are converted to Passenger Car Units (PCU), with exposure calculated as shown in equation (1). The constants (0.75 and 2.5) represent the PCU conversion factors for motorcycles and trucks, respectively, as specified in the Highway Capacity Manual.

$$\mathrm{VHT_i = t_i x(Minibuses_i + Motorcycle_i * 0.75 + P.Car_i + Truck_i * 2.5)} \tag{1}$$

Where:
$\mathrm{i -}$ traffic patterns,
$\mathrm{t_i}$ − time spent travelling in "i" ,
$\mathrm{VHT_i}$ − Vehicle Hour Travelled in "i" ,
$\mathrm{Minibuses_i}$ − volume of the minibus in "i" ,
$\mathrm{Motorcycle_i}$ − volume of motorcycle in "i" ,
$\mathrm{P.Car_i}$ − volume of the passenger car in "i" ,
$\mathrm{Truck_i}$ − volume of the truck − car in "i" .

Reckless driving rate (third step)
The frequency of reckless driving incident (RDE) is quantified relative to the time vehicles, expressed in Particular Car Unit (PCU), spend on the road (VHT) under each traffic condition (i). Therefore, the reckless driving rate (R) is defined as the number of reckless manoeuvres per 24 hours vehicle travelled, meaning the expected number of reckless driving events over 24 hours (one day) of vehicle activity in a given traffic condition, provided by equation (2).

$$\mathrm{R_i = \left({}^{RDE_i}/_{VHT_i}\right) * 24} \tag{2}$$

Contributing factors for reckless manoeuvres (fourth step)
Reckless manoeuvres are considered countable and random events; therefore, their occurrence within a given time interval is assumed to follow a Poisson distribution. Assuming the number of hazardous manoeuvres in each traffic pattern is proportional to the exposure in that specific traffic condition, the probability of observing a reckless manoeuvre in a particular traffic scenario is modelled as the product of traffic flow and exposure, as shown in equations (3) and (4). Factors that significantly contribute to their occurrence are identified with a p-value less than 0.05.

$$\mathrm{P(Y = y_i|\lambda_i t_i) = \frac{e^{-\lambda_i t_i}(\lambda_i t_i)^{y_i}}{y_i!},} \tag{3}$$

$$\mathrm{\lambda_i t_i = exp\,(a + b_1 x_1 + \cdots + b_n x_n) t_i,} \tag{4}$$

Where
Let, $\mathrm{t_i}$ represent the Exposure ($\mathrm{VHT_i}$),
$\mathrm{P(Y = y_i|\lambda_i t_i)}$: Probability of observing $\mathrm{y_i}$ reckless manoeuvre in the traffic pattern i,

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λ_i: Expected number of hazard manoeuvres per unit VHT in traffic pattern i,
x_k: The flow of each transport modes (k=1~n); Traffic flow at each pattern
a, b_k: Unknown parameters (k=1~n).

Result

Cluster of the traffic flow

Cluster analysis utilized four vehicle categories—particular cars, minibuses, motorcycles, and trucks—as independent factors. The Elbow Method identified three as the optimal number of clusters, as increases beyond this point did not significantly reduce the within-cluster sum of squares (WCSS), with the curve flattening and indicating diminishing returns in clustering performance, Figure 3; The K-means clustering method subsequently categorized the traffic stream conditions, as illustrated in Figure 4:

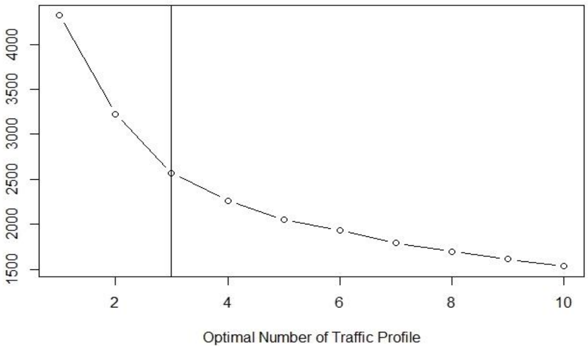

Figure 3
Elbow method. Optimal number of Traffic patterns

- Pattern 1: Motorcycle and Car Dominant Traffic (MCDT) - This pattern is characterized by a high traffic flow of motorcycles and particular cars, comprising 380 samples and representing 35.15% of the data.
- Pattern 2: High-Density Traffic (HDTf) - This pattern is marked by a higher traffic flow of minibuses, particular cars and trucks, consisting of 330 samples and accounting for 30.53% of the data.
- Pattern 3: Low-Density Traffic (LDTf) - This pattern is defined by a lower traffic flow of almost all vehicles categories, consisting of 371 samples and representing 34.32% of the dataset.

Based on the Kolmogorov-Smirnov test for normality, the observed counts of reckless driving

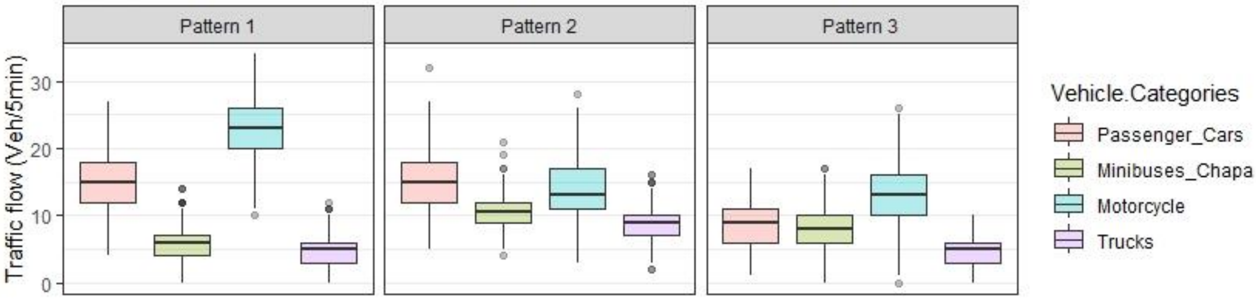

Figure 4
Traffic Patterns

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events (RDE's) do not follow a normal distribution (p-value < 2.2e-16); consequently, the Mann-Whitney U test was applied to assess whether significant differences exist in the frequency of reckless manoeuvres across the traffic patterns. A total of three comparisons were conducted, revealing a statistically significant difference in the frequency of reckless manoeuvres between at least one pair of patterns, specifically between Pattern 2 (High-Density Traffic) and Pattern 3 (Low-Density Traffic), Table 2.

Table 2
Mann-Whitney U test, comparison of the reckless driving behaviour across the traffic patterns

	Pattern 2 (HDTf)	Pattern 3 (LDTf)
Pattern 1 (MCDT)	0.437	0.1354
Pattern 2 (HDTf)		0.0269

Relationship between traffic patterns and reckless driving occurrence
For each traffic pattern, the rate of reckless driving (Equation 2) is estimated by normalizing the number of reckless driving events by the vehicle's hours travelled (VHT). The results indicate a higher likelihood of reckless driving events in Pattern 2 (HDTf), while Pattern 3 (LDTf) demonstrates a lower susceptibility to such occurrence, Figure .

Contributing factor for reckless driving occurrence
This analysis is based on the assumption that reckless driving events follow a Poisson distribution. To assess this assumption, both the mean and variance were evaluated. The assumption was confirmed as valid, as the difference between the mean (0.14) and variance (0.15) was not statistically significant (p-value = 0.094). Consequently, a Poisson regression model was employed to identify the vehicle categories that significantly contribute or are associated to reckless manoeuvres. The results, shown in Table 3, indicated that motorcycles, trucks and minibuses have positive statistically significant association with reckless manoeuvres. Specifically, a one-unit increase in the number of motorcycles in the traffic stream is associated with a 2.58% increase in reckless manoeuvres; similarly, a one-unit increase in the number of trucks corresponds to a 6.49% increase in reckless manoeuvres, and a one-unit increase in minibuses is associated with a 4.23% increase in reckless manoeuvres.

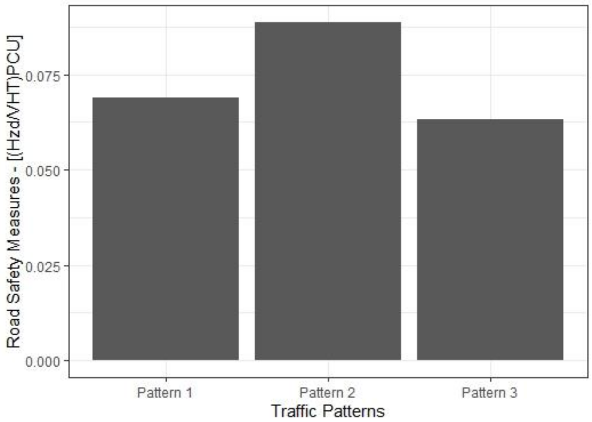

Figure 5
Likelihood of reckless driving across traffic patterns

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Table 3
Effect of vehicles categories on the hazard manoeuvres (model 1)

Factors (Vehicle categories)	**Coefficients**	**P-value**		
(Intercept)	-3.2901	< 2e-16	***	
Passenger Cars	0.0095	0.3537		
Minibuses "Chapa"		0.0414	0.0045	**
Motorcycle		0.0255	0.0008	***
Trucks		0.0629	0.0000	***
Number of samples 1081;		P-value: 3.721 e-08;		
Significance level: *** 0.1%, **1%, * 5% |		$\boldsymbol{\delta_f}$ - 2081.5/ $\boldsymbol{\delta_0}$ - 2098.5 (Log-likelihood)		

Applying the Poisson model to evaluate safety within the traffic stream, measured by the frequency of reckless driving events, across different traffic patterns—with Pattern 1 as the reference—the results presented in Table 4 reveal a statistically significant difference in reckless driving occurrences when traffic conditions shift from Pattern 1 to either Pattern 2 or Pattern 3. The frequency of reckless driving increases by 26.98%, with the shift to Pattern 2, and decreases 30.93% with the shift to Pattern 3.

Table 4
Reckless driving prediction with respect to traffic change (reference – pattern 1)

Factors (Traffic Patterns)	**Coefficients**	**P-value**	
(Intercept)	-1.9754	< 2e-16	***
Pattern 2 (HDTf)	0.2389	0.0106	*
Pattern 3 (LDTf)	-0.3701	0.0009	***
Number of samples – 1081;		P-value: 2.815 e-06;	
Significance level: . 10%; * 5% | likelihood)		$\boldsymbol{\delta_f}$ - 2086.05 / $\boldsymbol{\delta_0}$ - 2098.5 (Log-	

Discussion

Road accidents in Mozambique are estimated to claim the lives of at least three people each day, with reckless driving being one of the leading causes of these crashes (Romão et al. 2003). Reckless driving has been linked to various factors, including human behaviour, driving under the influence of psychoactive substances, and the driver's age and experience. However, there are few studies examining how traffic conditions themselves may contribute to reckless driving. This study addresses this gap by focusing on the city of Nampula, northern Mozambique.

To classify traffic conditions, this study categorizes vehicles in the traffic stream into four groups: particular cars, minibuses (specifically referring to public transport), trucks (including vehicles over four tons), and motorcycles. This categorization was implemented to facilitate vehicle counting, given the limited human resources available for the survey. On the other hand, reckless driving was identified as any of the following driving behaviour: sudden lane changes, abrupt braking, overtaking on both sides, overtaking on the left side, and failing to yield to the right side of the road.

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The k-means clustering method was applied to classify traffic conditions by identifying distinct patterns within the traffic stream. This classification was based solely on vehicle category data, allowing each pattern to reflect specific characteristics of the traffic stream determined by the penetration rate of each vehicle type. Three patterns were identified, Figure 4:

Pattern 1—Motorcycle and Car Dominated Traffic (MCDT)—is characterized by a high volume of motorcycle and particular car flow, with very few minibuses and other vehicle categories. This pattern likely represents traffic conditions observed during the early evening when minibuses reduce their operations and motorcycles become a more prevalent mode of transportation.

Pattern 2—High-Density Traffic Flow (HDTf)—is characterized by a high volume of nearly all vehicle categories, particularly minibuses, which operate at their maximum capacity. In contrast, motorcycles operate at a lower capacity. The high volume of other vehicles at maximum capacity can create risks for motorcycles, leading to a reduction in their activity.

Pattern 3—Low-Density Traffic Flow (LDTf), nearly all vehicle categories operate at their lower capacity.

Assuming each traffic pattern reflects a specific traffic condition, the rate of reckless driving events within the traffic condition has been estimated, as shown in Figure 5.

The elevated rate of reckless driving observed in Pattern 2 can be attributed to factors such as: 1) High Volume of Minibuses: Minibuses operate as demand-oriented public transport. When their numbers are high, drivers may engage in competitive behaviour to be the first to pick up passengers, often compromising safety. 2) High Volume of Trucks: The presence of a large number of trucks can hinder the normal movement of minibuses and motorcycles, thereby forcing these vehicles into hazardous manoeuvres. 3) Motorcycles in Heavy Traffic: Motorcycles, being less numerous and operating under heavy traffic conditions, often navigate in particularly risky environments. These combined factors contribute significantly to the increased incidence of reckless driving in this traffic pattern.

Pattern 1 represents the second highest risk condition, which can be attributed to similar competitive behaviour observed in Pattern 2. However, in this case, the competitive behaviour is primarily seen among motorcycle riders.

Pattern 3 is the safest due to its low traffic volume. The absence of competitive behaviour and the lack of traffic congestion contribute to a reduced likelihood of observing reckless driving behaviour.

Given that reckless driving manoeuvres are countable, independent events with equal mean and variance, they are considered to follow a Poisson distribution. Consequently, two Poisson regression models were developed: the first model assesses the factors contributing to the occurrence of reckless driving behaviour within the traffic stream, while the second model compares the occurrence of reckless manoeuvres across the different traffic patterns.

Model 1, presented in Table 3, indicates that an increase in the traffic flow of any vehicle category—minibuses, trucks, or motorcycles—leads to a significant rise in reckless manoeuvres. This can be attributed to heightened competition among these vehicles, particularly among minibuses and motorcycles, which both function as demand-oriented public transport. When their numbers increase, drivers and riders often accelerate to be the first to pick up passengers, frequently at the expense of safety. This competitive behaviour leads to reckless and aggressive driving.

In contrast, the influence of trucks on reckless driving is not due to the trucks themselves engaging in dangerous manoeuvres. Rather, the presence of trucks in the traffic stream acts as an impediment to both motorcycle riders and minibus drivers. As the number of trucks increases, they create obstructions that compel minibus drivers and motorcycle riders to adopt reckless and aggressive driving behaviours in an attempt to overtake these barriers.

Conclusions

This study aims to investigate how traffic conditions contribute to reckless driving behaviour within the traffic stream. While most existing research attributes reckless driving primarily to individual (human) factors, these studies often neglect the potential influence of the surrounding traffic environment on such behaviour. To the best of the author's knowledge, there are no studies specifically examining the impact of traffic conditions on the likelihood of drivers or riders engaging in reckless driving. This research seeks to address that gap, thereby contributing to the existing body of literature.

Understanding how traffic conditions shape reckless driving behaviour is essential for accident prevention, as the majority of accidents are linked to reckless, careless, and aggressive driving. In this study, reckless driving is defined as any of the following behaviours: sudden lane changes, abrupt braking, overtaking on both sides, overtaking on the left side, and failure to yield the right of way.

The traffic stream in this study was classified into three distinct patterns: Motorcycle and Car Dominant Traffic (MCDT), High-Density Traffic Flow (HDTf), and Low-Density Traffic Flow (LDTf). These traffic patterns were defined based on the volume of each vehicle category present within the traffic stream.

The study's findings reveal that reckless driving behaviour is significantly influenced by traffic conditions. Motorcycles, minibuses, and trucks are identified as key contributors to the occurrence of reckless driving. In high-density traffic flow conditions, where the volume of minibuses or motorcycles is higher, there is a greater tendency for reckless driving behaviours compared to conditions with lower traffic density.

The findings of this study are crucial for policymakers, highlighting the need for the following actions: 1) Establishing Policies for Minibus and Motorcycle Operation: Given that demand-oriented public transport systems, such as those for minibuses and motorcycles, tend to encourage competitive driving behaviours that often lead to the disregard of safety measures, it is essential to define and implement appropriate operational policies for these means of transport; 2) Creating Dedicated Lanes for Motorcycles and Minibuses: Mixed traffic conditions exacerbate competition among different vehicle categories, increasing the likelihood of reckless driving. Establishing dedicated lanes for motorcycles and minibuses could help to mitigate this issue, reducing conflicts and enhancing overall traffic safety.

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