Effect of Motorcycle Composition on Traffic Accident Rate in Mixed Traffic

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Abstract: Efforts to improve road safety in low- and middle-income countries must involve an understanding of local road characteristics. Mixed traffic is infamous for being accident-prone, yet most research on such problems has not focused on urban roads or considered motorcycles and other motor vehicles. This study investigates the contribution of motorcycle composition to accident rates in the context of Indonesia's urban mixed-traffic conditions. Urban road elements and traffic conditions were included in the analysis. Two accident models for motorcycles and motor vehicles were derived using negative binomial regression techniques at the mesoscale to account for over-dispersed count data. The results revealed that both accident rates shared similar contributing factors with different levels of significance. Furthermore, the motorcycle proportion and accident rate did not increase monotonically but tended to have the highest accident rate in mixed-traffic situations.

Keywords: Accident rate, motorcycle accident, negative binomial regression, traffic composition

1. INTRODUCTION

The disproportionate level of road deaths between low- and middle-income countries (LMIC) and high-income countries (HIC) is stark, based on data from 185 countries (WHO, 2015). Approximately 90% of road deaths occurred in LMICs, with just 10% occurring in HIC (Burton, 2013). Actions to improve such conditions are often ineffective as they are not based on local road traffic characteristics (Hills and Downing, 1980).

Local road traffic characteristics include road-user behavior, traffic composition, type of motor vehicles, and the road environment (Jacobs and Bardsley, 1977). Among motor vehicles, motorcycles tend to dominate the traffic stream in most LMICs, particularly in Southeast Asia. Table 1 provides traffic composition data for several LMICs. With the lack of affordable and reliable public transport, motorcycles have become a viable option due to their affordability and are considered to be more reliable during traffic congestion. Consequently, the shared use of space and time between motorcycles and larger motor vehicles on the roadways deems hazardous situations more prominent.

Research on road safety in mixed-traffic environments, the various vehicles, and road variations is still limited across and within Southeast Asia (World Health Organization, 2015). In Indonesia, research is limited to inter-urban roads and/or characteristic of motorcycle accidents. Consequently, the impact of motorcycle composition on accident rates in urban road networks with mixed-traffic conditions is not yet explored. Furthermore, encouragement to study traffic-volume composition and related accident rates stems from the following theory—that is, "accident risk is dependent on the composition of various road users" (Elvik *et al*., 2009). Different traffic compositions are known to impact driving behavior and road-user interaction,

as implied by Brüde and Larsson (1993), affecting traffic volume, capacity, and ultimately, safety. Based on fundamental traffic principles, we expected that as traffic flow increases, ultimately reaching its maximum flow rate, speed would increase; hence, the risk of accidents would likewise increase. After traffic volumes peak, speeds start to decrease; hence, the risk of accidents should decrease.

Table 1. Sample of traffic composition data (%)

Vehicle Type	Traffic composition (unit)			
	Indonesia	**India**	**Philippines**	**Vietnam**
Cars and 4-wheeled light vehicles	8,148,330 (11.209%)	15,313,000 (13.321%)	2,770,591 (41.758%)	556,945 (1.679%)
Motorized 2- and 3-wheelers	60,152,752 (82.749%)	82,402,000 (71.684%)	3,482,149 (52.483%)	31,452,503 (94.832%)
Heavy trucks	3,296,315 (4.535%)	6,041,000 (5.255%)	347,182 (5.233%)	552,244 (1.665%)
Buses	1,095,554 (1.507%)	1,486,000 (1.292%)	34,933 (0.523%)	97,468 (0.294%)
Others	0	9,710,000 (8.448%)	0	67,607 (0.204%)
Total	72,692,951	114,952,000	6,634,855	33,166,411

Source: Global status report on road safety (2013).

Mixed traffic in Indonesia is primarily based on the large number of motorcycle users in the traffic stream, motorcycles typically being used for daily short- and medium-range travel purposes, mainly in urban areas. However, it is not uncommon to use them for specific inter-urban travel purposes such as leisure. Consequently, the study of mixed traffic should be conducted on urban roads as compared to inter-urban roads. Because of that, other contributing variables in the study should characterize typical mixed-traffic situations and urban road networks. The urban road network consisted of roads with different hierarchies. In this study, arterial and collector roads were selected because varying traffic compositions between road users are more prevalent than on roads with lower utility. The selected roads were then divided into smaller units for analysis based on their road type.

The dependent and independent variables were allocated based on predetermined units of analysis. The multivariate analysis model was determined by considering the accident rate dispersion parameter of the dependent variables. The motorcycle and motor vehicle accident rates were selected for analysis, the analysis method using multivariate analysis to understand and compare how the selected explanatory variables contribute to accident risks (Lord and Mannering, 2010).

As a case study, this research focuses on an LMIC, particularly Bandung, West Java, Indonesia. Bandung was chosen as the study location as it is the third-largest city in Indonesia, as shown in Table 2. It has many motorcyclists, with 56% of road deaths being motorcyclists (based on 2018 data). Moreover, Bandung is practical since, other than the availability of accident data, the SINDILA project observes traffic automatically in several road segments in the city and road authorities and universities collect traffic-volume data for projects, research, and educational purposes, which may be of help in completing this research.

This study aims to clarify the effect of high motorcycle composition in mixed-traffic situations in an urban road network in Bandung, West Java, Indonesia. Furthermore, these new insights could enable the road authorities to better plan road safety countermeasures—for instance, the possibility of exclusive motorcycle lanes to improve safety.

2. LITERATURE REVIEW

Mixed traffic is often thought to be dangerous for road users, especially the more vulnerable road users such as motorcyclists and cyclists. However, accident studies that consider mixed-traffic conditions and the road-user composition of urban road traffic remain deficient, especially in Southeast Asia. The term mixed traffic has been used loosely in other studies. For example, research on shared spaces between personal-mobility vehicles and pedestrians is considered to be a mixed-traffic condition (Dias *et al*., 2017). Another example is research on the safety of urban arterial roads under mixed-traffic patterns conducted on the subject of large pedestrian and bicycle traffic-flow volumes (Ma *et al*., 2010).

However, in general, we can conclude that mixed traffic is a situation in which two or more road-user types in the traffic stream—with different static and dynamic characteristics—interact simultaneously. The ideal countermeasure for mixed traffic is lane segregation between vulnerable road users and others, as mentioned in an ADB (2003) report on vulnerable road users amongst Asian and Pacific road users. However, lane segregation as a traffic safety countermeasure may not always be viable, especially when science-based evidence to justify the effort is lacking. This research aims to provide such evidence by clarifying the relationship between motorcycle traffic composition and accident rates. Moreover, any discussion on mixed-traffic conditions is a discussion on road-user composition.

Research on mixed traffic composition are as follows: first, Tjhjono (2009) studied fatality rates in inter-urban roads that accounted for the proportion of motorcycles as one of the contributing variables but did not consider the proportion of other vehicle types or mixed-traffic conditions in an inter-urban road not being as prevalent as in an urban road. Second, Brüde and Larsson (1993) studied road accidents at a junction based on road users' different volume compositions. However, the study focused on pedestrians and cyclists at road junctions without focusing on other traffic conditions.

In a mixed-traffic context, other research has mostly tended to focus on the characteristics of motorcycle accidents. For example, Chiu, Chen, and Hsieh (2014) studied mixed-traffic flow characteristics, driver behavior, and traffic conflicts between motorcycles and automobiles without considering traffic composition, whilst Pai (2011) summarized motorcycle accident studies, mostly in developed countries. Motorcycle accident research is mainly focused on two topics: the first being motorcycle conspicuity under different lighting conditions, and second, being motorcycle gap times and time-to-arrival. Neither group discussed the traffic composition of their research.

The above situation holds in developing countries, including Indonesia. Hence, based on the above observations, there is not much research on traffic composition in traffic accidents with regard to local road characteristics. Abusini, Sulistio, and Wicaksono (2010), Wedagama and Dissanayake (2010), Sarm and Kanitpong (2016), and Iamtrakul, Hokao, and Tanaboriboon (2003) studied motorcycle accident characteristics using statistical modeling from the point of view of traffic volume and road geometry, time of occurrence, accident type, and road user profile and characteristics. Among these studies, only Abusini *et al*. considered traffic volume as an explanatory variable without considering the traffic composition of different road users.

Roads and traffic composition in urban environments are different from those in inter-urban environments. Firstly, roads in urban environments form a vast network compared to inter-urban roads, resulting in different operational characteristics and short-distance road segments limited by intersections. Secondly, because of uncontrolled urban development in Indonesia, the roadside is often used for parking or to conduct business, which affects the traffic flow, and even in urban or collector roads where road access limitation is essential, access density is high. Thirdly, roads in urban areas are interrupted by traffic flow, where vehicles often stop and move continuously during travel. Such stop-and-go movement, especially in a dense traffic flow, affects the smoothness of travel. Consequently, it is crucial to discern such characteristics when studying traffic composition and accident rates on urban roads.

Based on the previous paragraph's observations, we decided to use the mesoscale model to analyze traffic accidents in urban mixed-traffic situations. To fully understand the factors

affecting traffic safety, we included network centrality analysis, a two-fluid model, road types, roadside disturbances, access density, and signalized intersections. In this research, a review on mesoscale modeling is primarily based on Li and Wang's (2017) work, while some parts discuss network centrality from Jayasinghe's (2017) work. Two-fluid models developed by Prigogine and Herman (1971) have been found to correlate with many traffic factors, including traffic accidents.

Most accident studies treat intersections and road segments as separate units of analysis. However, in an urban-road network—which may have a high density of intersections located close to each other—such methods may not be appropriate (Li and Wang, 2017). The argument is that the interaction between a segment and an intersection cannot be adequately studied; hence, our proposal of a meso-level model that enables the analysis of both segments and intersections as a single unit of analysis.

Roads in urban environments form networks that affect their operational characteristics and accessibility, consequently affecting road safety (Li and Wang, 2017). The centrality parameters of betweenness centrality and closeness centrality represent the road network's topological characteristics. Betweenness centrality describes how centrally located a road is among other roads in a network; consequently, it captures pass-by movements, whereas closeness centrality describes how near other roads are to a specific road, representing the attraction and production of movements (Jayasinghe, 2017).

The state of traffic in an urban road environment can be expressed by moving and stopping states due to frequent traffic flow interruptions, the two-fluid model being able to depict both states (Prigogine and Herman, 1971). Various studies have shown that the two-fluid model correlates with road, driver, and vehicle traffic elements. Road-network features and road-user characteristics can be correlated using the two-fluid model (Herman and Ardekani, 1984). as can road-user characteristics (Williams, Mahmassani, and Herman, 1995) and accident occurrences, respectively (Dixit et al., 2011).

Typically, accident studies use count models to consider the nature of accident data with non-negative integer values, such as the Poisson, negative binomial, zero-inflated, and logit models. In choosing among these many models, an understanding of the available data alongside the model assumptions is essential. Considerations in choosing a model should involve analyzing its dispersion parameter and whether the data have a preponderance of zero values, along with the possibility of spatial or temporal correlation (Lord and Mannering, 2010).

As shown in Table 1, mixed traffic with a large proportion of motorcycles is a traffic phenomenon prevalent in Indonesia and in several other LMICs that is considered to be dangerous, especially for motorcyclists. The ideal solution would be to separate them from other road users. However, quantitative research on such matters, particularly in an urban context, is lacking. Furthermore, lane separation of motorcyclists from other road users is not always appropriate because of space or budgetary constraints. Consequently, this study aims to clarify the relationship between a high proportion of motorcycles and road safety.

3. METHODOLOGY

The analysis methodology consists of four steps. The first step is to divide the selected road network into meso units of analysis, and the second step is to allocate the obtained or estimated variables into each meso unit. Thirdly, the general data statistics and correlation analysis are checked, after which multivariate analysis is conducted.

In mesoscale modeling, there is no differentiation between a road segment and an intersection. The mesoscale is between the macro scale—which usually covers an area—and the microscale—which separates segments and intersections (Li and Wang, 2017). To obtain sufficient data, a 100 m unit analysis division was applied to the selected road using a mobile survey vehicle equipped with GPS, which was able to tag a designated road every 100 m during the survey. The variables included in this study were allocated to each unit of analysis.

In general, most of the variables used included location information, making it relatively simple to allocate them to a unit of analysis using the QGIS software application. However, some variables did not have location information—such as access density, signalized intersections, and road types. Consequently, additional measures needed to be taken to allocate each variable's value to the analysis unit for those variables—that is, assigning them to each associated meso unit (a 100 m unit division of the road overlay), using Google Maps to observe access density with Google Street View, and checking the analysis unit on Google Maps. The assignment of signalized intersections and road types was conducted similarly.

Before analysis, all the variables included in the study were checked for summary and correlation statistics. For the summary statistics—in addition to obtaining a summary of the variables on hand—the goal was to examine the dependent variable's mean and variance to decide which multivariate analysis would be appropriate for analysis. Correlation statistics detect highly correlated variables and avoid collinearity, while their signs guide the kind of relationships that can be expected between a dependent and an independent variable.

The final step was conducting multivariate analysis. This research analyzed each motorcycle and motor vehicle accident by building separate models using the same independent variables. Unfortunately, both dependent variables are in the form of an accident rate, not an integer. By contrast, most multivariate analyses of count data are for non-negative integers; thus, a functional form modification was required.

4. DATA DESCRIPTION

Considering the technical and practical aspects of this study, we chose Bandung to be the study location. From a technical perspective, Bandung is the third-largest metropolitan city in Indonesia with a vast urban road network, associated traffic safety problems, access to resources for obtaining secondary data and conducting surveys. An arterial and collector road in the road network should have no or limited connection with a lower-class road, ideally; however, in reality, this is not the case. The road configuration in the road network varies between the divided and undivided segments of two-way and one-way roads.

In general, the source of data for such variables comes from accident, traffic, and road data collected using various methods. Most of these variables need to be estimated before they can be used in any analysis. The data processing and collation methodologies are discussed in the following subsections.

4.1 Study Location

Overall, 16 road segments—varying in length—from the Bandung road network (Figure 1) were used in the study, each of which was divided into 100 m units of analysis using a meso-level approach combining road segments and intersections (Li and Wang, 2017). Li and Wang's division method was based on speed characteristics and geometry. However, in this research, applying the same approach was not practical because of the limitation of total road length with traffic volume data and other supporting data allowing the inclusion of roads in the analysis. Consequently, using Li and Wang's method resulted in a small analysis unit that could not be adequately analyzed.

The division into 100 m units of analysis used data collected from a mobile road survey vehicle belonging to the Institute of Road Engineering (IRE) in Bandung. The vehicle had a GPS feature to tag the location every 100 m while collecting visual and geometric road data on a designated route. The vehicle's location data were exported to a GIS software application as a reference location for the units and a reference to input other data into each analysis unit. This

division resulted in 479 observations. Moreover, visual data from the survey vehicle were used to obtain roadside disturbance data.

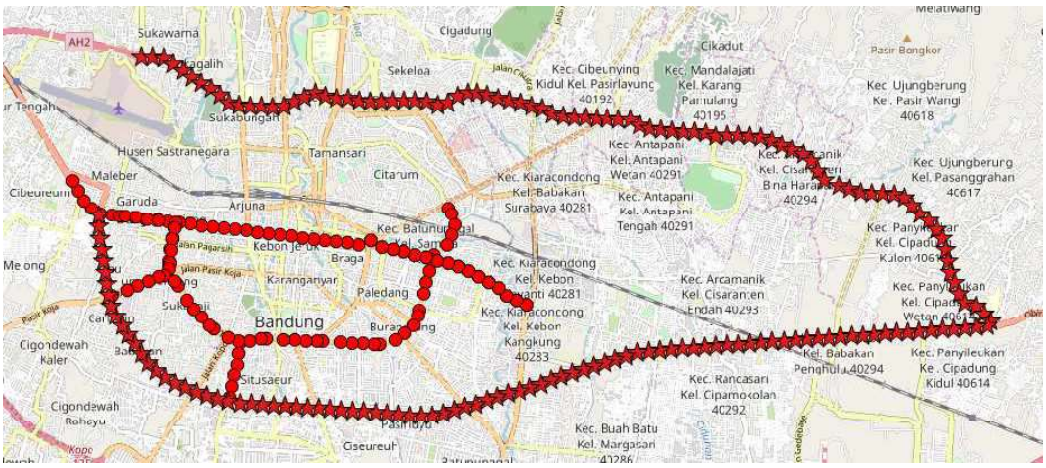

Figure 1. Study location in Bandung, West Java, Indonesia

4.2 Accident data

Accident data management in Indonesia is under the auspices of the Indonesia Road Safety Management System, accessible online at https://irsms.korlantas.polri.go.id/login. We obtained accident data from the Ministry of Public Works who accessed the system. To prevent "regression to the mean" in the analysis, five years of accident data (2013–2018) were used in this research.

Accident data provide information related to accident cases, including the location, time, vehicle type, road user profile, and general description of the cause of accidents. Unfortunately, not all accident cases are thoroughly investigated, usually only those accidents involving multiple vehicles and victims. By contrast, most cases designate a "general assumption" of the accident cause based on the testimony of road users, eyewitnesses, and a general understanding of the location and situation, emphasizing road users' behavior more than the traffic characteristics or road infrastructure. Consequently, this study did not consider accident cause information in the accident data, using only the location, number of accidents, and vehicle type.

The motorcycle accident count (MAC) and motor vehicle accident count (MVAC) were converted into accident rates using units of 100 million vehicle kilometers of travel (VKT). The conversion requires additional data, such as the length of the unit of analysis and traffic volume. Equation (1) describes the accident rate as follows:

$$AR = \frac{AC \; x \; 10^8}{l \; x \; n \; x \; AADT \; x \; 365} \qquad (1)$$

where:

AR = accident rate (100×10^6 VKT)
AC = accident count (vehicle)
l = segment length (m)
n = period of observation (years)
AADT = annual average daily traffic (vehicle/day)

4.3 Traffic data

Traffic volume data in Indonesia is not collected periodically, even on main roads. Consequently, traffic volume data are not readily available. So, we collected data from various sources to overcome these limitations: the first source, traffic volume data from the SINDILA project of the IRE, a camera-based traffic data collection project that has been running for more than five years. SINDILA camera locations exist in three segments within the case study—that is, Jl Dr. Djunjunan, Jl Pasupati, and Jl Soekarno-Hatta. The second source was traffic data collection from road authority/university research projects examining the same road segments. Since both data were surveyed in 2018 and there was only a slight annual change in the number of vehicles in the city of Bandung (Table 2). Accordingly, there was only a need to account for traffic variations within a year.

The collected traffic data came primarily from one observation point at each segment (the average length of each segment being 2.01 km). This may not be the ideal number of observation points. However, each observation considered the traffic flow into and out of the road segment by avoiding major intersections, to obtain the best possible representation of traffic flow. Only Jl Soekarno-Hatta (of length 18.35 km) comprised several sub-segments with four observation points across the segment. To cover sub-segments that did not have observation points, we used available data from the nearest sub-segment. The process of unification of the various traffic volume source data was as follows. First, the received data came with different survey times. For example, the SINDILA and Road Authorities data were complete 24-h data, but the SINDILA data were collected during one to two months of observation, while the government data were collected over a period of just three days. The data from the University was 12-h of data collected over a one-day period of observation. Second, from the complete 24-h data, an hourly average traffic volume was obtained by calculating the average directly. For the 12-h data, the average hourly traffic data needed to be adjusted. Calculation of the average annual daily traffic (AADT) involves multiplying the average hourly traffic volume by 24, the annual traffic variation (k) of 7%–12% being obtained from the Indonesian Highway Capacity Manual. We chose a k value of 9%. The formula for the calculation is available at formula (2). Third, we created a form for traffic volume file data, comprising road segment names, latitude and longitude, and traffic volume (motorcycle, passenger car, and heavy trucks) to unify different sources of traffic data. Fourth, input all calculated AADT values of each road segment to the file. Lastly, using QGIS, we plotted the data onto a map to be used as a reference, overlaying it with the road-division map explained in subsection 4.1.

$$\text{AADT} = \text{Average hourly traffic volume} \times 24 \times k \qquad (2)$$

Table 2. Yearly vehicle number variation (2015–2018)

Vehicle Type	Traffic composition (unit)			
	2015	2016	2017	2018
Cars and 4-wheeled light vehicles	369,373	399,862	-	402,649
Motorized 2- and 3-wheelers	-	1,251,080	1,328,783	1,256,057
Heavy trucks	70,293	-	76,098	73,569
Buses	6,061	-	6,748	6,390

Source: Bureau of Statistics (2021)

The research focused on how the high proportion of motorcycles—one of the vulnerable traffic modes making up mixed traffic situations—affected the accident rate. Consequently, we separated motorcycle proportions from four-wheel or more vehicle proportions (i.e., passenger cars and heavy vehicles), creating different variables for analysis purposes. Furthermore, the proportion of heavy vehicles was relatively small compared to motorcycles and passenger cars, we decided to place heavy vehicles and passenger cars into one group—that is, motor vehicles.

The traffic composition was allocated into 479 units of analysis based on the road name where the data were collected. The traffic composition initially included the motorcycle percentage (MCP) and motor vehicle percentage (MVP) in the analysis. However, because of the high correlation, only the MCP was used as an explanatory variable. Therefore, in the model, MCP was a categorical variable with the following arrangement: (1) MCP a is the motorcycle percentage from 52% to less than 63%; (2) MCP b is the motorcycle percentage from 63% to less than 73%; and (3) MCP c is the motorcycle percentage from 73% to 83%.

4.4 Two-fluid parameters with GPS data

The logic of using the two-fluid parameters developed based on Bose and Einstein's theory is due to its ability to represent traffic as a moving and stopping movement (Prigogine and Herman, 1971). Moving and stopping movements in urban road networks are caused by road characteristics, road user maneuvering, and unrestricted access to the main road.

The parameters of the two-fluid model are *Tm* and *n*. *Tm* is the minimum free-flow travel time when there is no stopping, and *n* is a parameter describing the network's operational resistance to degradation with increasing demand. Both parameters can be estimated using (3):

$$Tr = Tm^{1/n+1}\, T^{n/n+1} \tag{3}$$

where:
Tr = running time
T = total travel time

Parameter estimation comes from the moving and stopping times of a probe survey vehicle. Previous studies used different sampling strategies. For example, in some studies observations of 20–25 samples (one observation @ 1 km) using one vehicle were sufficient (Dixit *et al.*, 2011), whereas in others sampling requirements for the two-fluid model used 10–20 units of vehicles and a survey period of 10–15 min (Williams, Mahmassani, and Herman, 1995). The data collection method was a chase car method using GPS to collate the speed and travel time. This method required the selected survey vehicles to mimic random vehicles in the designated study locations. If a vehicle exited the designated route, the selected vehicle chose the nearest available vehicle to follow. The two-fluid model estimation procedure consists of acquiring data from GPS devices, dividing the data into 1 km micro-trips, identifying moving and stopping times, and summarizing each of these times for each micro-trip estimation (Yeon, 2005).

This research determined a benchmark based on previous research and available resources to obtain 20–25 observations for each road segment. However, because each road segment had considerably different lengths (the shortest was 0.89 km, while the longest was 18.35 km) and the roads in the case study were connected, it was decided that road segments with short lengths would be grouped into one combined segment. As a result, the new combination number of runs required to achieve 20–25 observations for the new combined segment varied between 2 and 2–5 runs (run = trip from the start to the end of a corridor). Based on the preliminary survey, the number of achievable runs per day per vehicle was four, and we were able to conduct the

survey for four days. Thus, the total number of observations per vehicle was approximately 160–200 observations. The details of the survey plan for the two-fluid model are summarized in Table 3.

The procedure for data collection using the two-fluid model was as follows: (1) we divided the road segments into two corridors; (2) we grouped the short road segments in each corridor into one combined segment; (3) we calculated the minimum run to achieve our targeted number of observations; (4) two car occupants and motorcycle pairs started from different directions to cover each side of the traffic flow; and (5) based on the chase car method, a motorcycle followed another motorcycle in the designated road segments, while a car followed another car in the designated road segments.

A survey vehicle in corridor 1 traveled 142 km for approximately 8 to 10 h—including resting time—while a survey vehicle in corridor 2 traveled 52 km for approximately 6 to 8 h—including resting time. Sixty-four data runs were collected using eight vehicles (four units of cars and motorcycles) over four days of observation. We divided the road segments into two corridors (Corridors 1 and 2). At each corridor, two pairs of motorcycles and cars collected data, starting from different directions to cover each side of the traffic flow. The motorcycles followed other motorcycles, while the cars followed other cars in the designated road segments.

Table 3. Two-fluid model survey plan

No.	Road segment	Length (km)	Grouping length (km)	No of runs for min 20-25 observation	Achievable run per vehicle per day	Achieved observations per day
Corridor 1						
1	Jl Soekarno-Hatta	18.35	18.35	2	4	40-50
2	Jl Dr Djunjunan	1.51				
3	Jl Layang Pasupati	2.89				
4	Jl Surapati	1.8				
5	Jl KHP Hasan M	2.37	8.57	3	4	40-50
6	Jl AH Nasution	4.19				
7	Jl Raya Ujung Berung	2.885				
8	Jl Cipadung	1.45	8.525	3	4	40-50
Sub total corridor 1		35.45				
Corridor 2						
9	Jl Laswi	1.21				
10	Jl Pelajar Pejunag 45	1.46				
11	Jl BKR	2.27				
12	Jl Peta	2.54	7.48	3	4	40-50
13	Jl Jamika	0.89				
14	Jl Jend Sudirman	1.95				
15	Jl Asia Afrika	1.51				
16	Jl Gatot Subroto	1.15	5.5	5	4	40-50
Sub total corridor 2		12.98				

The procedure for two-fluid parameter estimations is as follows: (1) extract data from the GPS device; (2) check for errors in the data; (3) calculate the cumulative moving distance; (4) divide the road segments into micro-trips; (5) calculate and summarize the moving and stopping time for each micro-trip; and (6) estimate the parameters. Two-fluid parameters were estimated using linear regression between the total running time per km as the dependent variable and travel time per km for each road segment. The formula can be expressed as (5), which is derived from (4). Subsequently, *Tm* and *n* can be obtained from (6) and (7). Two-fluid parameter estimation was carried out for the motorcycles and cars separately. The original intention of investigating different motorcycle and motor vehicle characteristics depicted by the two-fluid model would affect the accident rate—a result of the two-fluid parameter estimation shown in Table 4. A lower *Tm* indicates a high free-flow speed. From the results, the lowest *Tm* for motorcycles was at Jl Sudirman (0.556 min/km), while for cars it was at Jl Layang Pasupati (1.235 min/km)—the higher the *n* value, the faster the operational degradation of the road. The

highest *n* value for motorcycles was at Jl Sudirman, while for car occupants it was at Jl AH Nasution.

$$lnT_r = \frac{1}{n+1} lnT_m + \frac{n}{n+1} lnT \quad (4)$$

$$lnT_r = A + B\, lnT \quad (5)$$

$$n = \frac{B}{1-B} \quad (6)$$

$$T_m = e^{A/1-B} \quad (7)$$

where:
T_r = total running time
T = total travel time

Table 4. Two-fluid model estimation results

No.	Road segment	Motorcycle		Car occupant	
		Tm	n	Tm	n
		Corridor 1			
1	Jl Soekarno-Hatta	1.520	1.737	1.420	1.654
2	Jl Dr Djunjunan	1.485	5.606	1.363	2.383
3	Jl Layang Pasupati	1.249	13.762	1.235	4.622
4	Jl Surapati	1.887	1.934	2.221	1.937
5	Jl KHP Hasan M	1.531	5.606	2.303	1.999
6	Jl AH Nasution	1.921	2.472	1.752	15.042
7	Jl Raya Ujung Berung	1.864	0.723	2.167	2.452
8	Jl Cipadung	1.666	2.236	2.173	1.728
		Corridor 2			
9	Jl Laswi	1.598	0.515	1.81	0.934
10	Jl Pelajar Pejunag 45	1.416	0.623	1.781	0.732
11	Jl BKR	1.676	0.211	1.665	0.756
12	Jl Peta	1.463	0.5375	1.59	0.8055
13	Jl Jamika	1.599	1.381	1.924	1.991
14	Jl Jend Sudirman	0.556	14.366	1.744	3.214
15	Jl Asia Afrika	1.396	2.182	1.605	2.155
16	Jl Gatot Subroto	1.96	0.875	2.078	1.797

4.5 Road type and roadside disturbance

Originally, road type and roadside disturbances were intended to enter each analysis as an individual explanatory variable. However, there was a disparity in the frequency distribution among the sample data for both variables. Thus, we combined them into one variable. Here, we explain each variable individually, as well as the final combined variable.

The first explanatory variable is the road-type variable (RT). This study's road segments consisted of road types with three different configurations regarding the median and traffic direction. Therefore, to capture the effect of these different road conditions on the accident rate,

a categorical variable was proposed. Undivided roads were designated RT 1, while divided two-way roads were designated RT 2 and one-way roads RT 3. The sample data frequency distributions for each category were 146, 295, and 38, respectively. The second variable was roadside disturbance (RD). In this study, the basis of RD's formulation was that many legal or illegal roadside uses (including use of the outer lane) disturb the traffic flow. The form of the disturbance could be car parking or commercial activities on the roadside. The disturbance-blocking aspect of a roadway causes stop-and-go movements and encourages dangerous overtaking maneuvers. Another related situation is the entry and exit of vehicles in parking areas. This research considered only the existence of disturbance—that is, vehicles entering and leaving the roadside were not considered because of the difficulty in observing such behavior.

Data collection and calculation utilized the IRE survey vehicle, the video data including the visual conditions and coordinates. However, RD is a somewhat new concept in traffic accident research. A simple rule of thumb is necessary to ensure the consistent identification of RD. Firstly, the length of each disturbance was calculated for every unit of analysis. If the distance between disturbances was less than 1 m, they were considered to be a single continuous disturbance. Secondly, we calculated the width of the disturbance from the edge of the traffic lane to the outer edge of the disturbance position. Thirdly, a disturbance was considered to be rectangular, irrespective of the disturbance type or form. Finally, the dimension of the disturbance was calculated using GPS coordinates. The RD formula can be expressed as follows:

$$RD = \frac{\sum_{i=1,2,\ldots}^{n} (l_i \; x \; w_i)}{L_s} \tag{8}$$

where:

l_i = length of object *i*

w_i = width of object *i*

L_s = segment length

RD had a range of 6.07, and a variance of 0.298, with 90% of its value being less than 0.578. As mentioned previously, both variables have a sample frequency distribution problem, so it was decided to combine them. Visual examples are shown in Figure 2. The combined variable was deemed to be a road type and condition (RTC), a categorical variable with the following configuration: (1) RTC type a: undivided roads with an RD value between 0 to 6.07; (2) RTC type b: divided and two-way roads with an RD value between 0 and 3.44; (3) RTC type c: divided and two-way roads with an RD value between 3.45 and 6.07; and (4) RTC type d: one-way roads with an RD value between 0 and 6.07.

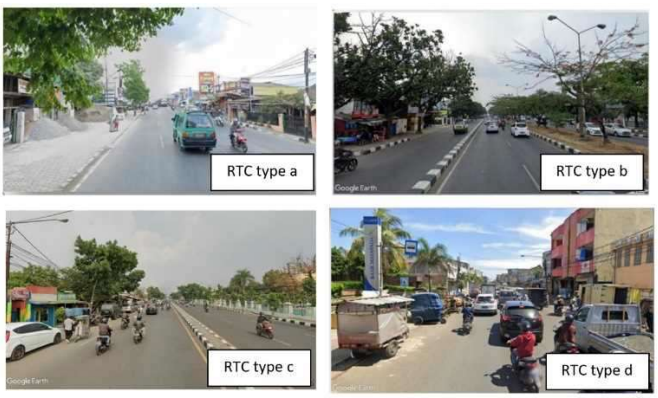

Figure 2. Image of each road type

4.6 Access density (AD) data

The location of arterial and collector roads under study should have limited direct access to properties. However, many roads have property access directly connected to roads due to uncontrolled urban development. Access density (AD) is a variable representing the number of direct access points from local roads or private/business establishments to the main road in a unit of analysis. The property of this variable is residential and business properties. The data collection method was observation using Google Maps and Google Street View. The calculation method was simple—that is, it used the 100 m GPS tag when forming the meso unit of analysis overlays in Google Maps. The street map feature was used to observe the access property, each of was recorded in an Excel spreadsheet.

4.7 Signalized intersection (SI) data

Conventional accident studies differentiate roads using straight segments and intersections. A signalized intersection (SI) primarily serves a high traffic volume and functions as a node between two or more main roads, typically using traffic signals. These intersections are deemed to be more prone to accidents because of their role in the road network and high-volume exposure. This study uses a meso-approach to define a unit of analysis that can combine the road segments and intersections to account for signalized intersections in the analysis and the introduction of the SI variable, which represents a signalized intersection and intersecting road in terms of the number of lanes. SI type A is a straight road segment; SI type B is a signalized intersection in which the intersecting road has two lanes, and SI type C is a signalized intersection where the intersecting road has three lanes or more. Unsignalized intersections are accounted for in the AD variable.

4.8 Network centrality (NC) with road network data

The concept of network centrality (NC) allows us to understand the importance of road links in a road network. There are several measures of NC. One of them is betweenness centrality, which refers to the extent to which a link belongs to the shortest path between any pair of nodes in a network—in other words, many of the shortest paths traverse that link (Porta, 2012). Betweenness centrality can be expressed as follows:

$$BC_{i[r]} = \frac{1}{(N-1)(N-2)} \sum_{j,k \in N, j \neq k, k \neq i} \frac{p_{jk(i)}}{p_{jk}} \tag{9}$$

where:

N = the total number of links in a network
RR = radius of the influence system considered
BCE = betweenness centrality of link *i*
pjk = number of geodesics between links *j* and *k*
$p_{jk(i)}$ = number of geodesics between links *j* and *k* that pass through *i*

The calculation of centrality also accounts for the size of the influence area. However, there are no guidelines for determining a suitable size of the influence area for accident studies, as no previous study has established a specific size (Li and Wang, 2017). Therefore, a large radius was set (10 km) as it was the closest round number (for distance) to the maximum distance of the study location radio network, which reached approximately 15 km. BY

comparison, a small radius of 1 km was considered to be the smallest radius of travel distance when using a motor vehicle. The calculation of NC was conducted using the Space Syntax Toolkit in QGIS (Gil, Varoudis, and Bartlett, 2014). As a result, the NC variable was coded to be 10 km (Betweenness centrality 10 km) and 1 km (Betweenness centrality 1 km).

5. RESULTS: MODEL DEVELOPMENT

Several well-known multivariate models for accident data include the Poisson regression, negative binomial regression, zero-inflated, and logistic regression models. To determine a suitable model and further develop it, it is essential to understand the data at hand. Descriptive statistics and correlation analysis are standard methods for understanding data, the results of which are listed in Table 5. Both dependent variables of the motorcycle accident rate (MCAR) and motor vehicle accident rate (MVAR) are less than the variance. The mean and variance of the MCAR were 5.317 and 41.965, respectively, whereas the mean and variance of the MVAR were 7.533 and 69.995, respectively. The results show that both the MCAR and MVAR exhibited overdispersion, suggesting that negative binomial regression would be suitable for this analysis. Furthermore, there was no sign of a zero value, wherein a zero-inflated model would be suitable.

All variables except for categorical variables were analyzed for correlation (Table 6) to evaluate the possibility of collinearity, gain insight into the correlation sign, and evaluate the strength of the linear relationships between variables. Unfortunately, the correlation between the MCP and MVP was high, and the two variables could not be entered into the model together. The inclusion was unfortunate because we aimed to determine how road users' different compositions affected the study's accident rate. Moreover, there was a high correlation between *Tm* and *n* for both motorcycles and car occupants with a correlation coefficient above 0.5; consequently, both variables need careful consideration when estimating the accident rate. In general, there are no other high correlations between the variables; the correlation of accident rate and accident count variables with other variables is low. However, this does not suggest that the results are insignificant.

Negative binomial regression is a count model, whereas the Poisson model assumes that the Poisson parameter follows a gamma distribution. The difference between them lies in the fact that Poisson regression requires that the means should equal the variance. Thus, it cannot handle overdispersion, whereas negative binomial regression techniques can account for it. Negative binomial regression as a count model deals with a non-negative integer independent variable. Because the accident rate is not a non-negative integer value, the exposure part of the accident rate input with the explanatory variables (with an offset function in the R software) was used. The accident rate was the accident count divided by the exposure—that is, the traffic volume exposure in a given observation period. The offset was a predictor in which the coefficient was set to 1, as shown in (10), in the basic form of a negative binomial equation. Equation (10) can be rewritten in the form of (11). Model development for motorcycles and motor vehicles was conducted using backward elimination, which does not produce a conclusion error; either a variable is significant, or it accepts a variable that explains the higher significant deviance when removed from the models (Tjahjono, 2009). The coefficient sign of the explanatory variables was checked based on the correlation analysis results when conducting backward elimination.

$$log(y) = intercept + a_1\ x_1 + a_2\, x_2 + \cdots + a_n\, x_n + log\, \varepsilon \quad (10)$$

$$\boldsymbol{log\left(\frac{y}{\varepsilon}\right) = intercept + a_1\ x_1 + a_2\, x_2 + \cdots + a_n\, x_n} \quad (11)$$

Table 5. Descriptive statistics

	MAC (case)	MVAC (case)	MCAR (10^6 VKT)	MVAR (10^6 VKT)	MCP (%)	MVP (%)
Minimum	0	0	0	0	52	18
1st quartile	1	2	1.468	2.001	65	27
Median	2	3	3.56	5.341	69	31
Mean	3.138	4.559	5.317	7.553	69.55	30.6
Variance	9.06	18.113	41.962	69.995	47.624	44.453
3rd quartile	5	6.5	6.784	9.781	73	35
Maximum	16	25	69.928	69.928	83	48
	TmCar (min/km)	**nCar**	**TmMc (min/km)**	**nMc**	**AD (count/100 m)**	**RD (m)**
Minimum	0.042	0.32	0.556	0.008	0	0
1st quartile	1.366	0.736	1.416	0.794	5	0
Median	1.644	1.728	1.494	1.258	8	0.114
Mean	1.699	3.021	1.539	2.847	8.374	0.267
Variance	0.233	49.978	0.085	18.256	23.825	0.298
3rd quartile	2.046	2.804	1.666	2.244	12	0.325
Maximum	2.617	50.37	2.108	23.329	25	6.072
	NACHr 10 km	**NACHr 1 km**				
Minimum	1.18	0.95				
1st quartile	1.372	1.274				
Median	1.413	1.316				
Mean	1.403	1.303				
Variance	0.003	0.007				
3rd quartile	1.445	1.356				
Maximum	1.483	1.456				

Table 6. Variable correlation results

	MCAR	MVAR	MCP	MVP	TmCar	nCar	TmMc	nMc	AD	RD	Choice 10 km	Choice 1 km
MCAR	1	0.956	0.075	-0.086	0.150	-0.058	0.052	-0.017	0.055	-0.073	-0.059	0.042
MVAR	0.956	1	0.064	-0.076	0.120	-0.053	0.058	-0.023	0.017	-0.080	-0.002	0.065
MCP	0.075	0.064	1	-0.991	0.330	0.016	0.130	-0.287	0.345	0.144	-0.098	0.019
MVP	-0.086	-0.076	-0.991	1	-0.304	-0.025	-0.165	0.290	-0.345	-0.154	0.081	-0.032
TmCar	0.150	0.120	0.330	-0.304	1	-0.529	0.346	-0.248	0.238	-0.094	-0.205	-0.035
nCar	-0.058	-0.053	0.016	-0.025	-0.529	1	0.107	0.167	0.046	-0.097	0.069	0.034
TmMc	0.052	0.058	0.130	-0.165	0.346	0.107	1	-0.515	0.093	-0.051	0.082	0.128
nMc	-0.017	-0.023	-0.287	0.290	-0.248	0.167	-0.515	1	-0.275	-0.157	-0.224	-0.417
AD	0.055	0.017	0.345	-0.345	0.238	0.046	0.093	-0.275	1	0.124	-0.168	0.145
RD	-0.073	-0.080	0.144	-0.154	-0.094	-0.097	-0.051	-0.157	0.124	1	0.088	0.121
Choice 10 km	-0.059	-0.002	-0.098	0.081	-0.205	0.069	0.082	-0.224	-0.168	0.088	1	0.311
Choice 1 km	0.042	0.065	0.019	-0.032	-0.035	0.034	0.128	-0.417	0.145	0.121	0.311	1

6. RESULTS AND DISCUSSIONS

The multivariate analysis using a negative binomial regression result is shown in Table 7. The results show that not all of the proposed explanatory variables were significant. Both the motorcycle and motor vehicle models shared similar significant variables—that is, MCP b, Choice 1 km, RT type B and C, and SI Type B. *Tm* car occupants was only significant in the motorcycle model. However, the motor vehicle model had more significant variables, including the additional variables AD and SI type C. Based on the Akaike information criterion (AIC), the motorcycle model was a slightly better fit than the motor vehicle model (2195.1, compared to 2510.9). Nevertheless, both models may not be the best models for prediction purposes,

judging from the standard error (0.168 for the motorcycle model and 0.135 for the motor vehicle model). Figure 3 shows the predicted accident rate vs. the observed accident rate for both motorcycle and motor vehicle models. The plotted data points clearly show that the model is not perfect, which can be further observed based on the histogram frequency of accident rates (Figure 4). The accident rate was less than 40 VKT for motorcycles and 15 VKT for motor vehicles, but in specific situations, the accident rate increased to 80 VKT and 30 VKT for motorcycles and motor vehicles, respectively. This study aims to clarify the effect of motorcycle proportion and typical urban road characteristics on accident rates rather than building predictive model. To that extent, we decided that the results were still beneficial. Furthermore, the addition of new roads is ideal for improving the model. However, it is impossible to expand the studied road network owing to data availability and time restrictions.

Table 7. Analyses results

Variables	Motorcycle		Motor vehicle	
	Coefficient	P>z	Coefficient	P>z
Intercept	–1.091	0.490	–1.352	0.377
MCP b	0.267	0.056*	0.226	0.095*
MCP c	0.240	0.118	0.180	0.229
Tm Car occupants	0.192	0.074*	0.143	0.173
Choice 1 km	1.263	0.039**	1.295	0.029**
Choice 10 km	0.601	0.588	1.133	0.294
RTC type B	–0.313	0.010**	–0.289	0.015**
RTC type C	–0.574	1×10^{-4} ****	–0.576	7.22×10^{-5} *****
RTC type D	0.025	0.908	–0.078	0.710
AD	–0.016	0.167	–0.019	0.079*
SI Type B	–1.152	0.005***	–1.067	0.004***
SI Type C	–0.370	0.106	–0.425	0.056*
AIC	2195.1		2510.9	
Standard error	0.168		0.135	

Significant codes: 0 '****' 0.001 '***' 0.01 '**' 0.05 '*' 0.1 ' ' 1

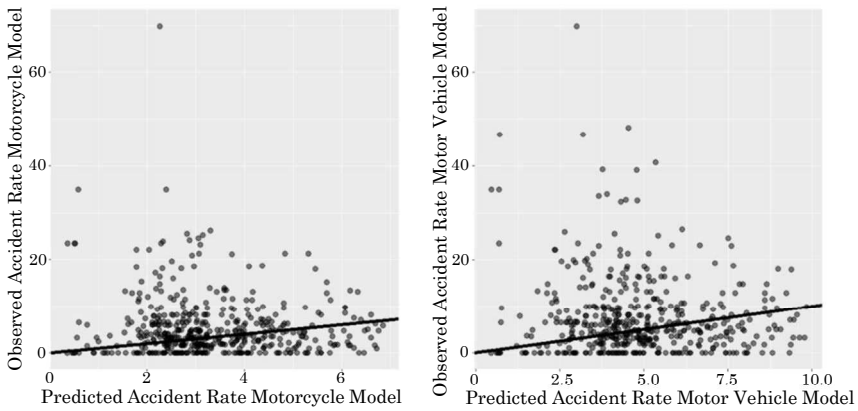

Figure 3. Predicted vs. observed accident rates (10 million VKT)

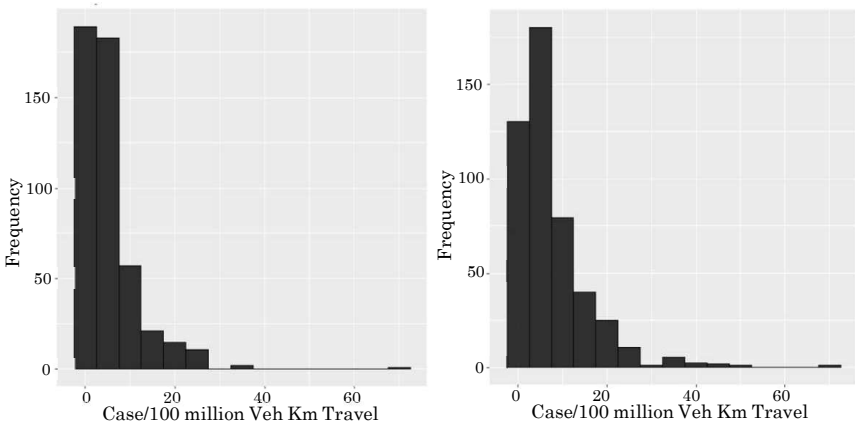

Figure 4. Histogram frequency of observed accident rates (10 million VKT)

The increasing motorcycle proportion contributes to increased accident rates for both motorcycles and motor vehicles, but not monotonically. The results showed that MCP b (motorcycle proportion from 63% to less than 73%) was significant but insignificant for MCP c (motorcycle proportion from 73% to 83%). Further investigation of the MCP and observed accident rates showed that the accident rate increased as the motorcycle composition increased. The peak accident rate occurred when the motorcycle proportion was greater than 50% (MCP a category), peaking when the motorcycle percentage was 73%, as shown in Figure 5. At this percentage, the ratio of motor vehicles to motorcycles was approximately 1:2 but considering the difference in motorcycle and motor vehicle size and the equivalent proportion of motorcycles, the spatial mixing ratio was approximately the same. Overall, this result supports the general notion that motorcyclists should be in a dedicated lane separated from other road users. However, it does not clarify how both could share the same space and time under particular conditions—such as low speed and appropriate composition (Asian Development Bank, 2003).

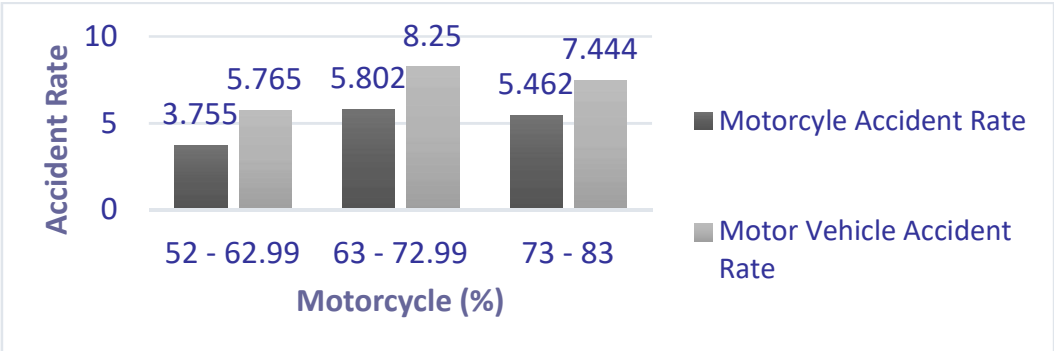

Figure 5. Histogram frequency of observed accident rates

Initially, *TmCar* and *TmMc* were expected in the model. The aim is to compare typical road user characteristics with respect to accident rates. Unfortunately, only *TmCar* entered the model because, when *TmMc* was in the model, other related variables coefficient sign changed compared to the sign from the correlation analysis. Furthermore, *TmCar* and *TmMc* showed a relatively high correlation. Previous research has shown that *Tm* has a negative correlation with *n* and accident rates. A lower *Tm* correlates with aggressive driving behavior, which quickly deteriorates traffic flow, represented by a higher *n*. As a result, the accident risk is higher (Dixit *et al*., 2011). However, the correlation result showed that *Tm* was positively correlated with

accident rate, even though it was still negatively correlated with *n*. This correlation indicates that in a condition where the free-flow speed is lower, limited aggressive driving of cars contributes to a higher accident rate. The *TmCar* occupants were significant only for the motorcycle model. The results indicate that car occupant driving characteristics contribute only to the motorcycle accident rate, concerning the counterintuitive coefficient sign. One possible explanation is that vehicles cannot maneuver freely under such traffic conditions. The slightest risky maneuvers potentially leading to accidents.

Further investigation of the observed data showed that *Tm* increases as motorcycle proportion increases (Figure 6); in a larger motorcycle population, aggressive driving becomes problematic. In such situations, dangerous movements or the slightest mistake can cause accidents. Two-fluid parameters were estimated for two kilometers of micro-trips for each road segment using probe data regarding the statistical significance. Even though the number of observations was set based on previous studies, there remained the possibility that the ratio of micro-trips and road segment length—particularly for short road segments—required additional observations.

Choice 1 km significantly contributes to the accident rate rather than 10 km. The results indicate that traffic analyzed within a 1 km radius of the road network significantly affects motorcycle and motor vehicle accident rates, while traffic within a 10 km radii is insignificant. Figure 7 shows that as the value of Choice 1 km increases—which indicates higher traffic—the average accident rate also increases. Through-traffic represented by choice is often considered to be accident-prone owing to higher exposure and speed.

The significant variables of RTC type b and RTC type c have coefficient signs according to expectations. Divided roads should exhibit better safety performance than undivided roads. The different RD values between both seems to have no material impact. RT type c, with its higher RD value, has a higher coefficient value than RT type b. RD is not significantly related to the accident rate because most of the recorded road disturbances already exist for an extended period; consequently, most road users are already aware of such conditions and can adapt to the situation accordingly. RDs may disrupt traffic flow but do not necessarily contribute to the accident rate. Figure 8 shows a typical roadside disturbance at the study location.

AD is significant only in motor vehicle models. However, the negative sign of AD was unexpected. An explanation for this is that road users drive more carefully on roads with high access to properties, primarily in commercial areas. AD is only significant for motor vehicle models because of motorcycle maneuverability to avoid disturbances caused by AD.

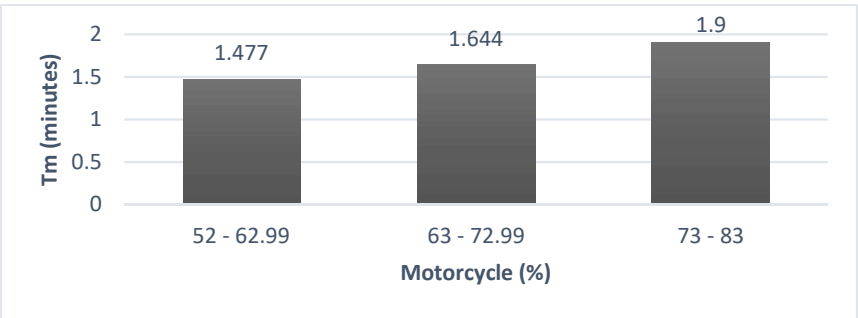

Figure 6. Average Tm and motorcycle (%)

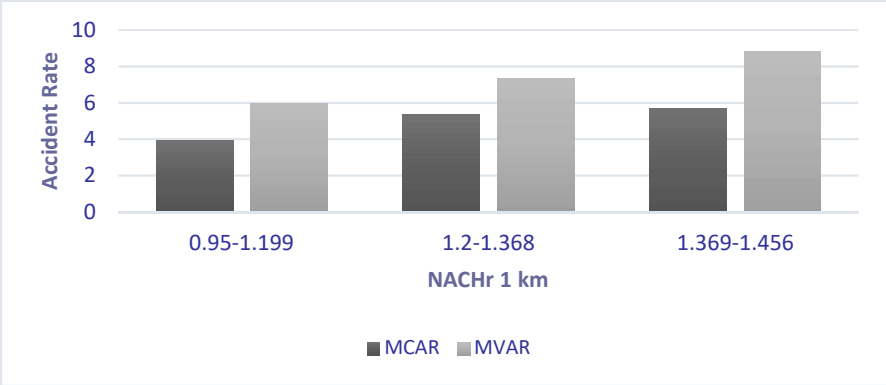

Figure 7. Choice 1 km and accident rate

Figure 8. Typical roadside disturbances

SI type B is significant for motorcycles and motor vehicles alike and has a negative contribution to the accident rate, while SI type C is significant only for the motor vehicle model. This finding is counterintuitive because it indicates that the intersection is safer than a straight section. However, the comparison was to SIs instead of non-SIs. This result may indicate that traffic control at an intersection contributes to safety. Applying an advanced stopping lane for motorcycles in many SIs in the study location would improve safety.

6. CONCLUSIONS

This study aims to clarify the effect of high motorcycle composition in mixed-traffic conditions using the mesoscale unit of analysis and negative binomial regression. The main findings were as follows:

Motorcycle and motor vehicles share some significant contributing factors to their respective accident rates, but also have differences. The results suggest that the motorcycle proportion and accident rate do not increase monotonically but tend to have the highest accident rates in mixed-traffic situations. The peak accident rate occurs when the motorcycle percentage ranges from 63% to less than 73%. The result suggests that the accident rate is at its highest when the motorcycle ratio is double that of motor vehicles. Whether a motorcycle and motor vehicle can safely co-exist in particular conditions, the aggregated data limitation cannot yet clarify. A study using high-resolution data or micro-level analysis should provide more information on the effect of traffic composition on the accident rate in mixed-traffic conditions.

Aggressive driving is represented by *Tm*, which is prevalent in Indonesia and is thought to impact the accident rate; in this case, it was significant only for the motorcycle model and

had a different coefficient sign from previous research concerning accident rates. This result may indicate that a car occupant moving at a low free-flow speed in a traffic situation causes aggressive motorcycle driving behavior.

The betweenness centrality confirmed that traffic generally contributes to accident rates. Choice 1 km for both motorcycle and motor vehicle models was more significant than Choice 10 km, indicating that traffic from the surrounding road network within a 1 km radii contributes more to the accident rate compared to traffic from within a 10 km radii.

The different significant variables between the motorcycle and motor vehicle models were related to road features, particularly AD and SI. Only RT shared similarities. Accident rates were lower in divided roads, with RD not contributing to them. SI and AD provided counterintuitive results. The study found that an SI had a more significant impact on the accident rate for both motorcycles and motor vehicles compared to a straight road segment. The effect of proper signal control and the installation of an advanced stopping lane for motorcycles may have some contributing impact.

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