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Factors Associated with Medium Trucks Casualties in the Special Region of Yogyakarta, Indonesia

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Abstract: With medium-duty freight trucks accounting for 37.39% of all freight truck crashes in DI Yogyakarta (the Special Region of Yogyakarta) Province, Indonesia, this study investigates the factors contributing to these accidents and quantifies their association with crash outcomes. Logistic regression analysis is used to predict the probability of a fatal crash based on various factors, including crash severity and potential causal relationships. The model examines the association between categorical variables and the odds of a fatal versus non-fatal crash, explicitly focusing on medium-duty freight truck involvement. The findings indicate that non-freight vehicle drivers experience 1.215 times higher odds of fatality compared to freight vehicle drivers. Additionally, passengers in truck crashes, including those involving medium-duty trucks, face an elevated risk of severe injuries. This study provides crucial insights into the factors influencing crash outcomes in accidents involving medium-duty freight trucks, necessitating targeted safety interventions.

Keywords: Truck safety, medium-duty trucks, fatal and non-fatal crashes, logistic regression, motorcycle crashes

1. Introduction

Freight vehicles, dominated by trucks, have been involved in a significant number of crashes that have resulted in fatal crashes. DI Yogyakarta (the Special Region of Yogyakarta) Province, Indonesia, has the highest crash number among the provinces in Java, where medium-duty trucks are involved in 37.39% of freight truck crashes [1]. This figure is comparable to that of Kentucky, USA, with 30% of light/medium truck driver crashes based on the crash first report of injuries [2]. Medium duty trucks refer to trucks which have a gross vehicle weight rating range of 14,000 lbs (6,350 kg) – 26,000 lbs (11,793) kg [3]. The figure indicates the urgency of finding the prevailing factors that cause the crashes. It is well understood that when trucks are involved, the severity of the crash increases due to the stronger impulse [4]. Several studies have been conducted on human factors [5], the accident severity by road types [6], and the spatial and temporal factors of crashes [7]. Studies on truck crashes have shown inconsistencies [8,9].

The prediction models were obtained using different variables under the causal factors, the severity of crashes and the severity of injuries [10,11]. The spatial and temporal effects on truck crash severity were found to be significant during the afternoon and nighttime [7]. Different approaches have been applied to create crash models, one of which is differentiating the outcome of a crash in terms of its occurrence or non-occurrence [9,12-14]. A mixed-logit model was developed as a baseline model to compare with the factors identified by three machine learning models [15]. Logistic regression was adopted to analyze how different factors influence crash severity, and it was found that the regression could provide significant interpretations [6]. Earlier, conditional logistic regression was adopted to investigate potential factors in severe injury or death in traffic crashes [13]. The SVM and random parameter logit model was adopted to study the severity of large truck involvement [16].

The present study analyses the various factors contributing to crashes involving medium-duty freight trucks and measures the strength of association between the causes and the crashes as the outcome. The expected result will address how each factor contributes to the crash and the probability of each factor that causes a fatal and non-fatal crash.

2. Data and Methods

The number of trucks as freight vehicles in Central Java is dominated by medium-duty trucks, leading to many crash involvements. The analysis uses 298 crash records from 2019-2021 as secondary data from the traffic police crash database IRSMS (Integrated Road Safety Management System). The data cover crashes occurring in all five districts of Jogjakarta: Bantul, Gunung Kidul, Kulon Progo, City of Jogjakarta and Sleman. Several factors which hypothetically have different effects on the probability of the occurrence of crashes were identified and grouped into the driver roles (truck driver, non-truck driver), number of victims, sites, year, day, time of day, road function, road types, road geometry and vehicle types. An analysis was carried out to measure the probability of a fatal crash based on various factors, such as different levels of crash severity and a plausible causal effect. As there was only one crash, the pedestrian crash was removed from the analysis. The severity of the level of injury in crashes does not include the loss of property.

Logistic regression is adopted in the analysis to predict the probability of a binary outcome, which in this study refers to fatal and non-fatal crashes. The predictors are qualities of the categorized factors. The regression analyzes the association between baseline categorical variables and fatal crashes. Binary responses are commonly studied in various fields to know how a predictor variable

$\boldsymbol{x_i}$ relates to a dichotomous response variable $\boldsymbol{y}$ $[-]$. The predictor describes the values of a particular factor that is assumed to have impacts on the response variable. The logistic model is a direct probability model where the assumptions are shown by transforming Prob $\{\boldsymbol{y} = \boldsymbol{1}\}$ to make a linear model in $\boldsymbol{\beta x}$.

Since the distribution of a binary random variable, $\boldsymbol{y}$ $[-]$, is entirely defined by the true probability that $\boldsymbol{y} = \boldsymbol{1}$ **a**nd since the distribution of the predictors was not assumed, the logistic model makes no distributional assumptions. The only assumption in the logistic model relates to the regression equation form as the model is a direct probability model. Unlike the assumption of multivariate normality using discriminant analysis, regression assumptions can be checked or proven true. The logistic model assumptions are most easily understood by transforming Prob$\{\boldsymbol{y} = \boldsymbol{1}\}$ into a linear model in $\boldsymbol{\beta x}$. With $\boldsymbol{z}$ as a linear combination of the input features, the logistic function is defined as [-]:

$$\sigma(z) = \frac{1}{1+e^{-z}} \quad [-] \tag{1}$$

The linear combination of inputs is given by

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots .. \beta_n x_n \quad [-] \tag{2}$$

where: β_0 is the intercept, $\beta_1, \beta_2, \ldots .. \beta_n$ are the coefficients [-], and $x_1, x_2, \ldots .. x_n$ are the input features [-]. The logistic regression model is then given by applying the logistic function to the linear combination of inputs:

$$P(y = 1|x) = \sigma(z) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2 + \ldots .. \beta_n x_n)}} \quad [-] \tag{3}$$

The log-odds (logit) transformation of the probability is given by:

$$logit\{y = 1|x\} \tag{4}$$

$$= log[P/(1-P)] \tag{5}$$

$$= \beta x \quad [-] \tag{6}$$

$$logit\{y = 1|x\} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \quad [-] \tag{7}$$

To estimate the parameters $\beta_1, \beta_2, \ldots .. \beta_n$ [-] the method of maximum likelihood was used.

$$L(\beta) = \prod_{i=1}^{m} \pi(x_i)^{y_i}[1-\pi(x_i)]^{1-y_i} \quad [-] \tag{8}$$

where m is the number of observations [-]. The log-likelihood function is:

$$l(\beta) = \sum_{i=1}^{m} [y_i log(P(y_i|x_i)) + (1-y_i) log(1-P(y_i|x_i))] \quad [-] \tag{9}$$

The parameter β_j is the change in the log odds per unit change in x_i if x_i represents a single linear factor that does not interact with other factors and if all other factors are held constant [-]. The regression coefficient (β_i) is calculated to give the estimated increase in the log odds of the *outcome per unit increase* in the value of the *exposure* [-]. The exponential function of the regression coefficient (e^{β_i}) is the odds ratio when the exposure is increased by one unit [-]. An odd ratio or log odds ratio quantifies the effects of a predictor. Therefore, the ratio can be constant and functions as a natural description of an effect in a probability model. The odds ratio is used to find the probability of an event's outcome when there are two possible outcomes and a plausible causal effect. As for crash outcome, the odds ratio measures the probability of a crash categorized as fatal or non-fatal.

3. Results and Discussion

The medium trucks involved in the crashes were predominantly minivans or medium trucks, while the non-truck vehicles were predominantly motorcycles. The significance of the associations between categorical variables was tested using the chi-square test. The sample was limited to drivers only for this analysis. Two factors are significantly associated with the probability of death: the driver's side in the crash (truck vs. non-truck) and vehicle types by participant. Among those who died, 96% were drivers of non-freight vehicles ($p<0.001$), and 81% were motorcycle drivers ($p<0.001$). Other associations are insignificant, but the road type factor has the lowest p-value ($p=0.2$). In our sample, 4/2 UD road type, which is a road with 2 lanes for each direction without a road median (undivided), was more common among fatal cases.

3.1 Full Logistic Regression

The descriptive statistics for assessing the association between characteristics and response are shown in the full logistic regression in Table 1. Response death is coded 1 and 0 if otherwise. All coefficients in tables are odds ratios, and the 95% CI for odds ratios are given in brackets.

Nighttime driving is exposed to a higher odds ratio than afternoon driving, as driving at night is risky and presents a significant challenge for many drivers. While various factors play a role, the dim lighting conditions at night are considered a primary reason for accidents with pedestrians and cyclists due to their limited visibility. Reduced visibility and lack of object conspicuity are commonly responsible for night crashes. Lack of conspicuity often results in rear-end crashes as the driver's spatial judgement and perception of other vehicles' dimensions, colour, and other physical appearance may be affected and miscalculated [17]. Nighttime driving poses unique challenges for truck operators, as reduced visibility can increase the risk of accidents and compromise the safety of drivers and other road users. Drivers often underestimate the visual impairments caused by low light conditions, leading to risky behaviour and a diminished ability to detect and respond to potential hazards. One key factor that can mitigate these risks is the quality and effectiveness of road lighting. Extensive research has explored the relationship between road lighting and truck safety, shedding light on how illumination can impact nighttime driving conditions [18-21]. Recent research also found that a significant proportion of truck crashes occur during the late night and early morning hours when lighting levels are lowest [22].

Table 1 Full logistic regression. Source: authors

	Reference Category	Death		Death Or Injury	
		Odds Ratio	95% CI	Odds Ratio	95% CI
(Intercept)		1.005	[0.772, 1.308]	1.179^{+}	[0.977, 1.422]
Role: Non-Truck Driver	Truck Driver	1.296*	[1.038, 1.619]	2.485***	[2.121, 2.912]
Role: Passenger	Truck Driver	1.806*	[1.109, 2.942]	2.929***	[2.068, 4.147]
N_Participants		0.977	[0.908, 1.051]	0.949*	[0.901, 1.000]
District: Gunung Kidul	Bantul	0.902	[0.783, 1.039]	1.083	[0.979, 1.198]
District: Kota Jogjakarta	Bantul	0.895	[0.738, 1.085]	1.015	[0.885, 1.165]
District: Kulon Progo	Bantul	0.921	[0.808, 1.049]	1.016	[0.926, 1.115]
District: Sleman	Bantul	0.983	[0.879, 1.100]	0.982	[0.907, 1.064]
Year 2020	Reference Year	1.007	[0.911, 1.112]	0.974	[0.908, 1.046]
Year 2021	Reference Year	0.992	[0.901, 1.093]	0.978	[0.913, 1.048]
Day: Weekend	Weekday	1.053	[0.961, 1.154]	1.022	[0.958, 1.091]
Time_Of_Day: Dawn	Afternoon	0.975	[0.859, 1.107]	1.002	[0.916, 1.097]
Time_Of_Day: Morning	Afternoon	0.993	[0.905, 1.091]	1.008	[0.943, 1.078]
Time_Of_Day: Night	Afternoon	1.045	[0.934, 1.170]	0.992	[0.916, 1.075]
Road_Functions: Collector	Arterial Road	1.008	[0.883, 1.151]	0.989	[0.899, 1.087]
Road_Functions: Local	Arterial Road	0.994	[0.839, 1.178]	1.014	[0.899, 1.145]
Road_Types: 4/2 D	2/2 UD Road	1.009	[0.867, 1.175]	0.986	[0.884, 1.099]
Road_Types: 4/2 UD	2/2 UD Road	1.138^{+}	[0.994, 1.304]	1.027	[0.932, 1.132]
Road_Geometry: Curve	4-Arm Intersection	1.225	[0.947, 1.584]	1.071	[0.892, 1.286]
Road_Geometry: Straight	4-Arm Intersection	1.022	[0.885, 1.180]	1.003	[0.906, 1.111]
Road_Geometry: T	4-Arm Intersection	1.101	[0.914, 1.325]	1.022	[0.896, 1.167]
Road_Geometry: Y	4-Arm Intersection	0.941	[0.597, 1.483]	1.018	[0.736, 1.408]
Vehicle_Types: M. Cycle	Medium Truck	0.953	[0.751, 1.209]	1.017	[0.858, 1.205]
Vehicle_Types: Pickup	Medium Truck	1.042	[0.927, 1.171]	1.005	[0.924, 1.092]
Vehicle_Types: Van	Medium Truck	1.042	[0.844, 1.286]	1.090	[0.938, 1.267]
Vehicle_Types: Other	Medium Truck	1.016	[0.832, 1.240]	0.933	[0.809, 1.076]
Num.Obs., R^2		262, 0.166		262, 0.838	
AIC, BIC, Log.Lik.		134.5, 230.8, −40.232		−42.8, 53.5, 48.421	

The regression results are significant at 0.1% (***), 1% (**) and 5% (*) levels. The "+" symbol suggests that this coefficient is significant at the 10% level (p-value < 0.1), meaning it is statistically different from 0 at the 90% confidence level. This indicates a non-zero baseline probability of the "Death Or Injury" outcome, even when all other factors are held constant.

Weekends show 1.053 times higher odds of death and 1.022 times higher odds of death or injury compared to weekdays. The figures may show that weekends experience different traffic patterns and driver behaviours than weekdays. The R^2 for death risk is 0.166, and for death or injury risk is 0.838. The RMSE for death risk is 0.28, and for death or injury risk it is 0.20.

The odds of a fatal outcome for a crash participant are 11.18%, 0.129 times higher for 4/2 UD road type compared to 4/2 D road type. Driving along curves increases the probability of death as it has an odds ratio of 1.225 times higher than the odds of driving at 4-arm intersections, which is the reference category. The presence of a median divider increases safety as it reduces potential head-on collisions and sideswipes with on-coming vehicles, as confirmed by a study by Fattah et al. [23]. The results show that the remaining variables are the most predictive in fatal crashes involving trucks. The 4/2 UD road type is significant in explaining the probability of crashes causing death. This finding aligns with that of Li et al. [15], who studied large truck crashes and found that medians can prevent severe crashes. The passing sight distances required for safe overtakes are significantly impacted by the presence of large trucks, as their length and acceleration/deceleration characteristics can pose challenges for other vehicles, as was also emphasized by Andanu et al. [24]. Driving along curves increases the probability of death as it has an odds ratio of 1.225 times higher than the odds of driving at 4-arm intersections. It is also clear that driving along curves poses the highest risk of death among all road geometries. Curves are, in many cases, below standards and do not provide the driving safety needed. With the relatively large dimensions, the turning radius of trucks often requires additional lanes or lane widening at curves. A previous study found that curves and truck volume were important features that contribute to accidents [25]. The condition, which is commonly termed dimension and overloading (ODOL) to enlarge the volume of the truck, has caused traffic accidents in Indonesia and is a national focus of traffic safety programs [26]. Insufficient superelevation for a certain operational speed and radius is also a potential hazard which can lead to accidents. Motorcycles are more susceptible to death or injuries than trucks, as seen in the higher odds ratio of 1.017. Pickups and vans are exposed to higher risk and the probability of death, as shown by the odds ratio 1.042. The dimensions of commonly used pickups and vans are those of passenger cars.

3.2 Stepwise Logistic Regression

The stepwise regression was conducted to fit the model from all predictor variables by entering and removing predictors. The final result was obtained after no other justifiable reason was given to enter or remove the rest of the variables. The R^2 of the linear regression formula for Death or Injury is 0.829, indicating that it is easier to explain the probability of any adverse outcome (death or injury) compared to the fatal outcome (vs. any other outcome). Non-truck drivers have 1.215 times higher odds of death and 2.483 higher odds of death or injury (compared to truck drivers). The corresponding ratios for non-truck passengers are even higher - 1.672 and 2.855, respectively.

Each additional participant (i.e., in fact, passenger) decreases the odds of death by around 6% (OR=0.943), which can be explained by the fact that more passengers are usually carried by larger vehicles that suffer less than, e.g. motorcycles in crashes involving truck vehicles. Characteristics based on other categories, such as districts, time, and road function, show different odds ratios but are insignificant in explaining the effects on the casualties at 0.1%, 1% and 5%.

Linear Regression Formula for Death (stepwise):

$$\log(\text{odds of Death}) = 0.994 + 1.215 * \text{role non-freight vehicle driver} + 1.672 * \text{role Passenger} + 0.992 * \text{road types 4/2 D} + 1.118 * \text{road types 4/2 UD [-]} \quad (10)$$

Linear Regression Formula for Death or Injury (stepwise):

$$\log(\text{odds of Death or Injury}) = 1.206 + 2.483 * \text{role non-freight vehicle driver} + 2.855 * \text{role passenger} + 0.943 * \text{n participants [-]} \quad (11)$$

These formulas represent the log-odds of the outcomes (Death or Death or Injury) as a linear combination of the predictor variables. The sensitivity of the regression model to changes in the input variables for predicting the different outcome is shown in Fig. 1.

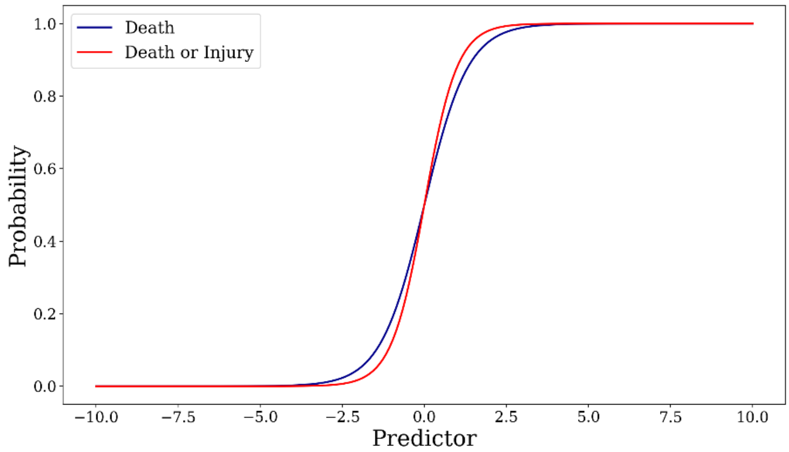

Fig. 1. Sigmoidal curves for the logistic regressions. Source: authors

The results of the linear regression models for "Death (stepwise)" and "Death or Injury (stepwise)" provide significant insights into the factors influencing the likelihood of death or injury in vehicular incidents. The coefficients, expressed as odds ratios, reveal the relative impact of various roles and road types on the outcomes.

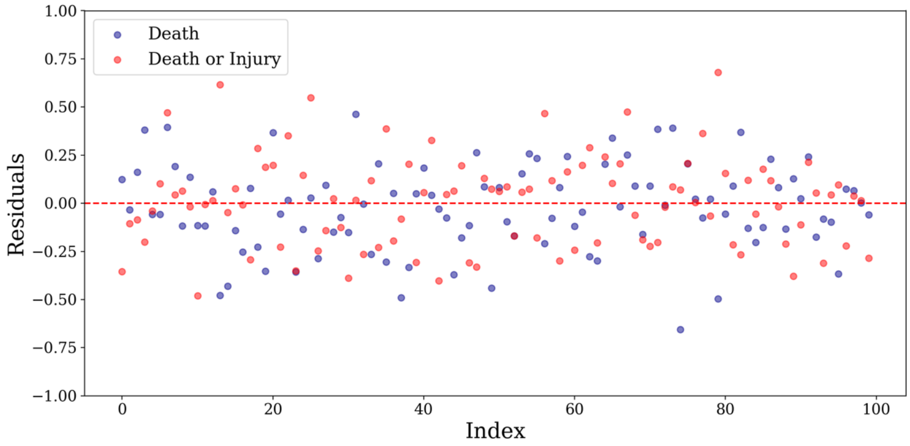

Fig. 2. Residual plot. Source: authors

In the "Death (stepwise)" model, the intercept of 0.994 indicates the baseline log odds of death when all other variables are zero. The role of the non-freight vehicle driver has a coefficient of 1.215, suggesting that the odds of death are 1.215 times higher for non-freight vehicle drivers compared to the reference category, likely freight vehicle drivers. This finding underscores the increased vulnerability of non-freight vehicle drivers in fatal incidents. Similarly, the role of passengers shows an even higher coefficient of 1.672, indicating that passengers are at a significantly higher risk of death, with odds 1.672 times greater than the reference category. The figure could be due to the lack of control passengers have over the vehicle and their reliance on the driver's actions.

The road-type variables also provide critical insights. The coefficient for 4/2 D road type is 0.992, slightly less than 1, indicating a marginal decrease in the odds of death for this road type compared to the reference. In contrast, 4/2 UD road type has a coefficient of 1.118, suggesting that the odds of death are 1.118 times higher on these roads. These findings highlight the importance of road design and conditions in influencing fatality risks. Roads with undivided lanes (UD) may present higher risks due to potential head-on collisions and other hazards. In the "Death or Injury (stepwise)" model, the intercept of 1.206 sets the baseline log odds for the combined outcome of death or injury. The role of the non-freight vehicle driver has a substantial coefficient of 2.483, indicating that the odds of death or injury are 2.483 times higher for non-freight vehicle drivers. This significant increase underscores the heightened risk these drivers face, possibly due to factors such as vehicle size, speed, and exposure. The role of passengers is even more pronounced, with a coefficient of 2.855, suggesting that passengers are at very high risk, with odds 2.855 times greater than the reference category.

This finding emphasizes the need for passengers to be provided with enhanced safety measures, such as improved seatbelt usage and airbag deployment. The number of participants in an incident also plays a crucial role, with a coefficient of 0.943, indicating that for each additional participant, the odds of death or injury decrease by a factor of 0.943. The decrease could be interpreted as larger groups potentially having a protective effect, possibly due to increased visibility and caution among drivers. The model statistics further validate the robustness of these findings. The R-squared values of 0.126 for the "Death (stepwise)" model and 0.829 for the "Death or Injury (stepwise)" model indicate the proportion of variance explained by the models. The higher R-squared value for the latter model suggests a better fit and greater explanatory power. The AIC, BIC, Log-Likelihood, F-statistic, and RMSE values provide additional measures of model performance, with lower AIC and BIC values indicating better model fit.

The random dispersion of residuals in Fig. 2 suggests that the models do not suffer from apparent patterns of heteroscedasticity (non-constant variance of residuals) or autocorrelation (correlation of residuals with themselves over time). The plot indicates that both models ("Death" and "Death or Injury") are performing reasonably well with no evident patterns or systematic errors. The random scatter of residuals around the zero line suggests that the assumptions of linearity and equal variance are likely satisfied.

4. Conclusion

The results show the significance of various parameters in the odds of the binary outcome. The role of drivers, whether the victim is a truck driver or a passenger, is significant in predicting injury severity. The role of being the truck driver does not predict either outcome. The role of being the non-truck driver has a higher probability of death or injury outcome than death outcome, indicating the high vulnerability of non-truck drivers in crashes with trucks. The higher odds ratios of non-truck passengers signify that the passengers are exposed to higher risks of any outcome than the drivers. The results also clearly indicate that passengers are highly exposed to severe injuries when involved in truck crashes, which necessitates related regulations of traffic management. Appropriate safety measures for freight vehicles, particularly medium trucks, must be developed. Conversion from undivided to divided roads can be expected to reduce deaths due to crashes involving medium trucks. The findings underscore the need for targeted interventions to enhance safety for non-freight vehicle drivers and passengers and road design improvements to mitigate risks. The results can guide policy-making, enhance safety regulations, and shape public awareness campaigns focused on decreasing road fatalities and injuries. The present research considers something other than fatigue and work hours of the truck drivers as the study focused on the road geometry variables. Investigating the relationship between driver fatigue, work hours, and accident rates is a potential area for future research.

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