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Finding the Factors Influencing the Severity of Traffic Accident Victims in Sleman Regency Using Ordinal Logistic Regression Analysis

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ABSTRACT

Special Region of Yogyakarta (Daerah Istimewa Yogyakarta, DIY) is well-known for its tourist, cultural, and educational attractions, but it also has a high accident rate. Sleman Regency is among the DIY regions with the greatest number of traffic accidents. To stop the rising number of people injured in road accidents, this issue needs to be taken into account. The objective of this study was to examine the profile of traffic accidents that happened in Sleman Regency between January and April of 2023 and use the ordinal logistic regression method to find characteristics that influence the severity of traffic accidents. Sleman Regency traffic accident data was used in this study. The opponent's vehicle factor, with the category of four or more wheeled vehicles and non-motorized vehicles, is one of the elements that influences the severity of traffic accident victims in Sleman Regency, according to the study's results. It is intended that local governments will be able to use the study's results as a guide when deciding what measures to take to lower the number of traffic accidents.

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A. INTRODUCTION

The rising number of traffic accidents in Indonesia each year has elevated them to the third-largest cause of death in the country, trailing only tuberculosis and coronary heart disease (Hidayati & Hendrati, 2017). The number of accidents increases along with the growing number of motorized vehicles in Indonesia. Traffic accidents affect traffic flow and traffic operations, and causing serious injuries and even fatalities. The World Health Organization (WHO) has stated that 1.25 million people die every year worldwide because of traffic accidents (Aqib et al., 2020). Between 20 and 50 million individuals experience injuries each year because of road traffic collisions, and a significant number of them end up with disabilities resulting from these injuries (Bahiru et al., 2018). It is evident that road traffic accidents have emerged as one of the leading causes of death and injury worldwide. The prevention and prediction of traffic accidents have become major topics in the fields of traffic science and intelligent vehicle research (Yang et al., 2023).

According to Law of the Republic of Indonesia Number 22 of 2009 concerning Road Traffic and Transportation, a traffic accident

is an unexpected and unintentional event on the road involving vehicles with or without other road users resulting in human casualties or property damage (Law of the Republic of Indonesia No. 22 of, 2009). Traffic accidents are events involving other road users, either unexpected or intentional. An accident is not a random occurrence; it is accompanied by an identifiable cause, allowing for preventive action to be taken.

Special Region of Yogyakarta (Daerah Istimewa Yogyakarta, DIY) is a popular tourist destination with a lot of cultural and educational offerings, but it also has a high accident rate. Under the jurisdiction of the DIY Regional Police, there were 5,420 traffic accident cases in 2022, totaling IDR 23,867,402,885 in losses. Sleman Regency had more traffic accidents than Bantul, Kulon Progo, Gunung Kidul, and Yogyakarta, according to data from the DIY Central Bureau of Statistics. Yogyakarta City had 490 incidents, Bantul Regency 1,557 accidents, Kulon Progo Regency 786 accidents, Gunung Kidul Regency 762 accidents, Sleman Regency 1,825 accidents. Yogyakarta's Sleman Regency has one of the highest rates of road accidents. Because of this, the research uses Sleman Regency traffic accident data (Statistics Indonesia, 2023). Table 1 presents an analysis of the number of accidents compared.

Table 1. Number of Regency/City Traffic Accidents in DIY in 2022

Regency/City	Number of Minor Injuries	Number of Major Injuries	Number of Death	Total	Material Losses (IDR)
Bantul	1,000	1	31	1,557	558,511,800
Kulon Progo	708	12	18	786	21,468,345,763
Gunung Kidul	513	0	18	762	666,255,004
Sleman	605	7	30	1,825	931,120,318
Yogyakarta	448	8	0	490	243,170,000
Total	3,274	28	97	5,420	23,867,402,885

According to reports of traffic accidents, nearly 90% of accidents are caused by human factors, and humans become one of the most unstable factors in causing traffic safety problems. Traffic accidents are often related to the driver's driving behaviour, which is mainly decided by his or her character, such as age, driving experience, and driving style (Hu et al., 2020). Many factors can influence traffic accidents, including traffic conditions, violations of existing traffic laws by drivers, driving at high speeds, a lack of a driving licence, failure to obey traffic signs and road markings, and various other forms of violations Wicaksono et al. (2014). Traffic accidents need to be a shared concern among various stakeholders. Conducting a more in-depth analysis of the factors influencing traffic accidents is crucial for obtaining reliable results. These results can then serve as a basis for formulating effective policies to reduce the incidence of traffic accidents.

To find factors that influence traffic accidents, one way to do this is through regression analysis. Regression analysis is a statistical process that estimates the relationship between variables, including techniques for modelling and analysing several variables based on the form of the relationship between one or more dependent variables and one independent variable (Armstrong, 2012). The issue is that categorical data is present in traffic accident data. Common regression analysis cannot handle the presence of categorical data. Using logistic regression is one solution. Logistic regression has various types, including binary logistic regression, multinomial logistic regression, and ordinal logistic regression. This research discusses ordinal logistic regression applied to traffic accident cases. Ordinal logistic regression is used to model the relationship between an ordered multilevel dependent and independent variable. In the modelling, the values of the dependent variable have a natural order or ranking (Lu et al., 2019). Ordinal logistic regression is a regression analysis used to analyze the relationship between the dependent variable, which is polycotomous with an ordinal scale, and the independent variable (Zain & Zakariyah, 2015).

Several researchers have conducted research on traffic accidents using ordinal logistic regression. Maylinda & Permana (2019) used the ordinal logistic regression analysis method to determine the factors that influence the severity of traffic accident victims in Padang City. Silvia et al. (2015) uses ordinal logistic regression to classify the severity of traffic accident victims in Semarang. Addini et al. (2022) uses ordinal logistic regression to classify the risk level of accident losses based on driver characteristics in Bali. Referring to previous research and based on the earlier description that the Special Region of Yogyakarta has a high accident rate, this study will discuss the factors influencing the severity of traffic accident victims using logistic regression. This discussion on traffic accidents in the Special Region of Yogyakarta is a novel contribution, as it has not been addressed before.

In this study, we chose the ordinal logistic regression method to understand the relationship between the dependent variable, which has more than two categories, and the independent variables. The model used for ordinal logistic regression is a logit model known as a cumulative logit model. The case involves a dependent variable with more than two ordinal categories, specifically the severity of traffic accident victims, classified into three levels: accidents with minor injuries, accidents with severe injuries, and accidents resulting in death. Given the high number of traffic accidents in Sleman Regency, researchers conducted an analysis using

the ordinal logistic regression method to determine the factors significantly affecting the severity of traffic accident victims in Sleman Regency from January to April 2023.

B. RESEARCH METHOD

This research utilizes secondary data of traffic accident victims from January to April 2023, obtained through the traffic accident reports of the Sleman District Police, accessed on June 6, 2023. The dependent variable (Y) used is the severity level of accident victims (minor injuries, serious injuries, and fatalities), and there are 9 independent variables used, namely age (0-25 years old, 26-45 years old, and more than 46 years old), driver's license (yes and no), time (crowded and deserted), gender (male and female), victim's role (rider, passenger, pedestrians, and cycling), type of accident (front-front, side collision, front-end, single vehicle accidents, hit-and-run, and other), victim's profession (self-employed, private employee, student, housewife, civil servant, teacher, and other), opponent's vehicle (motorized vehicle, four wheel vehicle/more, and non-motorized vehicle), and the victim's vehicle (motorized vehicle, four wheel vehicle/more, and non-motorized vehicle). The analysis methods employed in this research include descriptive analysis and Ordinal Logistic Regression Analysis. Descriptive analysis was conducted to provide an overview of the profile of traffic accidents in Sleman Regency from January to April 2023, while Ordinal Logistic Regression Analysis aimed to identify factors influencing the severity of traffic accident victims. The data is then processed using the ordinal logistic regression method with the following steps, as the flowchart is presented in Figure 1.

1. Descriptive Statistics

Descriptive analysis, as defined by Misbahuddin & Hasan (2022), is a form of research data analysis used to test the generalization of research results based on one sample. The variables employed for descriptive analysis include one or more independent variables, and it does not involve forming comparisons or relationships. Descriptive statistics are part of statistics that play a role in data collection, presentation, and interpretation of data both in graphic and descriptive form, so that the data presented can be easily understood or read.

2. Ordinal Logistic Regression

Ordinal logistic regression is an analytical method used to describe the relationship between the dependent variable (Y) and several independent variables (X). The dependent variable is ordinal, having more than two categories, with each category being rankable (Hosmer & Lemeshow, 2000). The model used in ordinal logistic regression is a logit model characterized by cumulative probability. The cumulative logit model is one that can be compared with the cumulative probability, specifically the probability that is smaller or equal to the j response category on i independent variables, denoted as $P(Y \leq j)$. The cumulative probability is defined as shown in Equation 1, —

$$P(Y \leq j) = \frac{\exp(a_j + \Sigma_{k=1}^{p} \beta_k x_k)}{1 + \exp(a_j + \Sigma_{k=1}^{p} \beta_k x_k} \tag{1}$$

— where $P(Y \leq j)$ is the value of the cumulative probability of the j response category, α_j is a constant value where $j = 1, 2, \ldots, K-1$, and $\beta_1, \beta_2, \ldots, \beta_k$ is the value of the regression coefficient. According to Benoit (2012), if there are several response categories, then K-1 logit functions will be formed. Based on the cumulative probability, the probability per response category will be obtained, as expressed in Equation 2.

$$\begin{aligned} P\left(Y = 1\right) &= \frac{\exp(\alpha_1 + \sum_{k=1}^{p} \beta_k x_k)}{1 + \exp(\alpha_1 + \sum_{k=1}^{p} \beta_k x_k)} \\ P\left(Y = j\right) &= \frac{\exp(\alpha_j + \sum_{k=1}^{p} \beta_k x_k)}{1 + \exp(\alpha_j + \sum_{k=1}^{p} \beta_k x_k)} - \frac{\exp(\alpha_{j-1} + \sum_{k=1}^{p} \beta_k x_k)}{1 + \exp(\alpha_{j-1} + \sum_{k=1}^{p} \beta_k x_k)} \\ P\left(Y = K\right) &= 1 - \frac{\exp(\alpha_K + \sum_{k=1}^{p} \beta_k x_k)}{1 + \exp(\alpha_K + \sum_{k=1}^{p} \beta_k x_k)} \end{aligned} \tag{2}$$

3. Independence Test

The independence test is a test used to determine the relationship between the independent variable and the dependent variable. One widely known method for analyzing categorical data is the chi-square test (χ^2). This test is valuable for assessing

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differences in observations, estimating the frequency of an observation within a specific category, and detecting relationships between a characteristic and other characteristic in a contingency table. The test is conducted using the chi-square test, and the test statistics utilized in the independence test are outlined in Equation 3.

$$\chi^2 = \sum_{i=1}^{I}\sum_{j=1}^{J} \frac{(n_{ij} - \hat{e}_{ij})^2}{\hat{e}_{ij}} \tag{3}$$

The decision criterion for this test is to reject H_0 if $\chi^2(count) > \chi^2(table)$ or if the significance value is less than α. This study adopts a significance level of α (0.05) with the following hypotheses:

H_0: There is no relationship between the dependent variable and the observed independent variable.

H_1: There is a relationship between the dependent variable and the observed independent variable.

4. G Test (Overall)

According to Hosmer & Lemeshow (2000), the overall test is conducted to examine the role of each independent variable in the model together or in other words to determine whether the independent variable has an overall effect on the dependent variable. To obtain a decision, the test value of G is compared with the value $X^2_{(\alpha,p)}$ with the rejection criterion of rejecting H_0 if the value of $G > X^2_{(\alpha,p)}$. The test statistics used are shown in Equation 4.

$$G = -2\ln\left[\frac{likelihood\ (model\ B)}{likelihood\ (model\ A)}\right] \tag{4}$$

5. Wald Test

The Wald test was conducted to test whether the independent variables were able to influence the dependent variable in the research. The significance level used is 5% or 0.05. The Wald test statistic follows a normal distribution, so to obtain the test decision results by comparing the W value with the $Z_{\frac{\alpha}{2}}$ value. The hypothesis used is to reject H_0 if $|W| > Z_{\frac{\alpha}{2}}$ or if the $p - value\ < \alpha$. The Wald statistical formula is contained in Equation 5.

$$W = \frac{\hat{\beta}_j}{SE(\hat{\beta}_j)} \tag{5}$$

6. Backward Elimination

Backward elimination is a step backward by regressing all independent variables with the dependent variable. The elimination process targets independent variables with a significance value exceeding the α (0.05) threshold. The backward step involves systematically removing variables with high significance values one by one, and this process is repeated until all variables have significance values less than α (0.05) (Maulidina et al., 2021).

7. Model Interpretation

The interpretation of coefficients in the ordinal logistic regression model can be accomplished by utilizing the odds ratio (OR). The odds ratio represents the ratio between the likelihood of an event occurring in a case group compared to a control group. In interpreting ordinal logistic regression coefficients, the odds ratio used expresses the comparison of risk levels among two or more categories on an explanatory variable, with one of the categories serving as a reference. The interpretation of the model is conducted by initially calculating the odds ratio obtained from $\exp(\beta)$ (Putri & Budyanra, 2020).

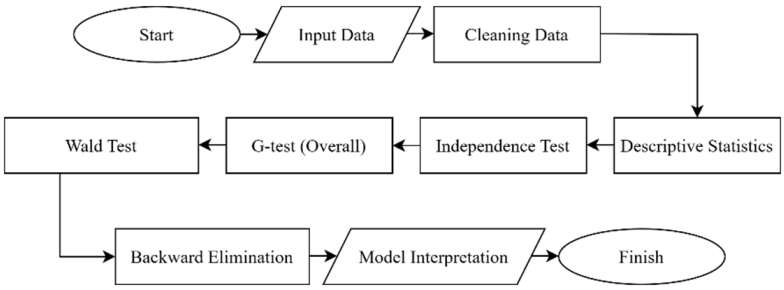

Figure 1. Conceptual Framework of the Research

C. RESULT AND DISCUSSION

1. Overview of January-April 2023 Traffic Accidents in Sleman Regency

The severity of the victims' injuries is categorized into three levels: minor injuries, serious injuries, and fatalities. Research data indicates that traffic accidents predominantly result in minor injuries, constituting the highest percentage at 75.98%, followed by victims with severe injuries at 20.72%, and fatalities at 3.30%. Additionally, there is a fluctuation in the number of traffic accidents in Sleman Regency from January to April 2023. In January, there were 314 accidents, followed by 173 in February, 30 in March, and 120 in April. The variation can be attributed to increased traffic, especially during the New Year's celebration holiday at the beginning of the year, leading to elevated vehicle mobility and consequently, a higher number of accidents in January. Subsequently, from February to March, there was a decline in accidents due to the approach and implementation of the month of Ramadan, prompting a reduction in outdoor activities. However, in April, there was a surge in accidents due to the commencement of the Eid homecoming flow, leading to increased vehicle traffic, particularly on roads such as Jalan Magelang, Jalan Wates, and Jalan Solo (Janati, 2023).

2. Independence Test

The results of the independence test of the victim's severity with the variables age, driver's license, time, gender, victim's role, accident type, victim's profession, opponent's vehicle, and victim's vehicle are shown in Table 2.

Table 2. Independence test of victim severity with independent variables

Variables	df	χ^2 count	χ^2 table	P − value	Decision
Age	4	8.471	9.488	0.076	Fail to Reject H_0
Driver's License	2	4.516	5.991	0.105	Fail to Reject H_0
Time	2	6.720	5.991	0.035	Reject H_0
Gender	2	5.582	5.991	0.061	Fail to Reject H_0
Victim's Role	6	29.085	12.592	0.000	Reject H_0
Type of Accident	10	57.943	18.307	0.000	Reject H_0
Victim's Profession	14	26.026	23.685	0.026	Reject H_0
Opponent's Vehicle	4	42.074	9.488	0.000	Reject H_0
Victim's Vehicle	4	20.075	9.488	0.000	Reject H_0

The results show that the variables of time, victim's role, accident type, victim's profession, opponent's vehicle, and victim's vehicle have a χ^2_{count} value that is greater than the χ^2_{table} value and a p-value that is each smaller than α (0.05) which means reject H_0 so that it can be concluded that using a confidence level of 95% there is a relationship between the severity of traffic accident victims in January-April 2023 in Sleman Regency with time, victim's role, accident type, victim's profession, opponent's vehicle, and victim's vehicle.

3. G Test (Overall)

G-Test is a likelihood ratio test used to test the role of the independent variables in the model jointly carried out with the G-Test. The results obtained from the simultaneous test are shown in Table 3.

Table 3. Independence test of victim severity with independent variables

df	G	χ^2_{table}	P-Value
20	107.91	31.410	0.000

Table 3 shows that the G value is 107.91, the χ^2_{table} value is 31.410, the df obtained is 20, and the p-value is 0.000. This means that the value of $G\ (107.91)\ >\ \chi^2_{(0.05,20)}(31.410)$ or p-value $(0.000)\ <\ \alpha\ (0.05)$, it can be concluded that with a confidence level of 95% the existing data reject H_0, meaning that there is at least one variable that has a significant effect on the severity of traffic accident victims.

4. Wald Test

The Wald test is used to test the parameters partially, using the results of the Wald statistic to test the effect of the independent variables of time, victim's role, type of accident, victim's profession, opponent's vehicle, and victim's vehicle partially on the dependent variable of the severity of traffic accident victims. The results obtained from the partial test are contained in Table 4.

Table 4. Independence test of victim severity with independent variables

Variable	Value	P-Value	Decision
Victim's Role: Passenger $(X_{5(2)})$	0.667	0.005	Reject H_0
Type of Accident: Hit-and-Run $(X_{6(5)})$	-1.920	0.002	Reject H_0
Opponent's Vehicle: Four-Wheeled Vehicles/More $(X_{8(2)})$	0.812	0.001	Reject H_0
Victim's Vehicle: Four-Wheeled Vehicles/More $(X_{9(2)})$	0.909	0.002	Reject H_0

Based on Table 4, which has a significant status means that the variables are factors that affect the severity of victims of traffic accidents, namely the victim's role (passenger), type of accident (hit-and-run), opponent's vehicle (four-wheeled vehicles/more), and victim's vehicle (four-wheeled vehicles/more) variable. While the other variables are results that do not have a significant effect on the dependent variable, this is indicated by the p-value which is greater than the α value (0.05).

5. Backward Elimination

The results of the backward elimination process until a significant variable is obtained are listed in Table 5.

Table 5. The process of Backward Elimination

Variable	Category	P-value					
		Start	Model 1	Model 2	Model 3	Model 4	Model 5
Time	Deserted	0.704	0.904	**0.866**	-	-	-
Victim's Role	Passenger	0.005	0.001	0.006	**0.006**	-	-
	Pedestrians	0.894	0.727	0.738	**0.736**	-	-
	Cycling	0.894	0.596	0.772	**0.774**	-	-
Type of Accident	Side Collision	**0.929**	-	-	-	-	-
	Front-End	**0.699**	-	-	-	-	-
	Single-Vehicle Accidents	**0.327**	-	-	-	-	-
	Hit-and-Run	**0.002**	-	-	-	-	-
	Other	**0.565**	-	-	-	-	-
Victim's Profession	Self-Employed	0.101	**0.059**	-	-	-	-
	Private Employee	0.151	**0.100**	-	-	-	-
	Student	0.557	**0.560**	-	-	-	-
	Housewife	0.299	**0.223**	-	-	-	-
	Civil Servant	0.627	**0.392**	-	-	-	-
	Teacher	0.914	**0.984**	-	-	-	-
	Other	0.915	**0.964**	-	-	-	-
Opponent's Vehicle	Four-Wheeled Vehicles/More	0.001	0.000	0.000	0.000	0.000	0.000
	Non-Motorized Vehicle	0.515	0.000	0.000	0.000	0.000	0.000
Victim's Vehicle	Four-Wheeled Vehicles/More	0.002	0.009	0.002	0.002	**0.003**	-
	Non-Motorized Vehicle	0.532	0.376	0.272	0.271	**0.065**	-

Backward model selection involves systematically removing variables one by one, starting with the ones with the highest p-value. The red mark in Table 5 shows the largest p-value in the last model, which is more than the significance level α (0.05),

so the backward process is carried out at that stage. The backward process concludes when all remaining variables have a p-value less than the significance level α (0.05). The results obtained from backward elimination are shown in Table 6.

Table 6. The result of Backward Elimination

Variabel	Value	P-Value	Decision	Description
Opponent's Vehicle: Four-Wheeled Vehicles/More $(X_{8(2)})$	0.828	0.000	Reject H_0	Significant
Opponent's Vehicle: Non-Motorized Vehicle $(X_{8(3)})$	-2.590	0.000	Reject H_0	Significant
Minor Injuries — Serious Injuries	1.138	0.000	Reject H_0	Significant
Serious Injuries — Fatalities	3.434	0.000	Reject H_0	Significant

After knowing the influential variables, the next is to form the final ordinal logistic regression in traffic accident cases in January-April 2023 in Sleman Regency after backward and simultaneous and partial parameter testing results in variables that have a significant effect, namely the opponent's vehicle, the logit function model obtained is:

$$Logit\ 1 = 1.138 + 0.828X_{8(2)} - 2.590X_{8(3)}$$
$$Logit\ 2 = 3.434 + 0.828X_{8(2)} - 2.590X_{8(3)}$$

The factors that influence the severity of traffic accident victims in Sleman Regency are the opponent's vehicle factor for four-wheeled vehicle/more, and the opponent's vehicle factor for non-motorized vehicle. Based on the logit value, the probability of the severity of traffic accident victims can be calculated.

Table 7. Probability of victim severity

Independent Variable	Minor Injuries	Serious Injuries	Fatalities
Opponent's Vehicle (four-wheeled vehicle/more)	0.877	0.109	0.014
Opponent's Vehicle (non-motorized vehicle)	0.190	0.510	0.301

Based on Table 7, it can be observed that the probability of opponent's vehicle with four-wheeled vehicle/more experiencing minor injuries is 0.877, the probability of serious injuries is 0.109, and the probability of fatality is 0.014. Meanwhile, the probability of opponent's vehicle with non-motorized vehicle experiencing minor injuries is 0.190, the probability of serious injuries is 0.510, and the probability of fatality is 0.301.

6. Model Interpretation

The odds ratio value based on the severity of the victim's injury and the category of the opponent's vehicle, the interpretation of the model containing the odds ratio value are shown in Table 8.

Table 8. Odds ratio

Variable	Odds Ratio
Opponent's Vehicle (four-wheeled vehicle/more)	2.290
Opponent's Vehicle (non-motorized vehicle)	0.075

The odds ratio value contained in Table 8 is obtained for victims of traffic accidents with opponent's vehicle (four-wheeled vehicle/more) have a risk of experiencing accidents from minor injuries to serious injuries or from serious injuries to fatalities by 2,290 times than victims of traffic accidents using motor vehicle. This means that the risk of victims of accidents with opponent's vehicle types (four-wheeled vehicle/more) is greater than that of victims of accidents with opponent's vehicle types (motorcycles). Furthermore, victims of traffic accidents with opponent's vehicle (non-motorized vehicle) have a risk of experiencing accidents from minor injuries to serious injuries or from serious injuries to fatalities of 0.075 times that of victims of traffic accidents using motor vehicle. This means that the risk of accident victims with the opponent's vehicle type (motorized vehicle) is greater than accident victims with the opponent's vehicle (non-motorized vehicle).

Research by Maylinda & Permana (2019) shows that the age of the victim, type of accident, and opponent's vehicle are factors that influence the severity of traffic accident victims in Padang City. Research by Silvia et al. (2015) indicates that the age of the victim and opponent's vehicle are factors influencing the severity of traffic accident victims in Semarang City. Research by Addini et al. (2022) demonstrates that opponent's vehicle, gender, education level, religion, and age of the victim are factors

affecting the severity of traffic accident victims in Bali. Each area has its characteristics, including traffic characteristics. In the Special Region of Yogyakarta, the factor that influences the severity of traffic accident victims is opponent's vehicle factor, with the category of four or more wheeled vehicles and non-motorized vehicles. As one of the areas in DIY with the highest traffic accident rate, it is necessary to study further related factors that can affect the severity of traffic accident victims in Sleman Regency. In addition, it is required to conduct an analysis using other methods as a comparison of the ordinal logistic regression used in this study.

D. CONCLUSION AND SUGGESTION

Based on the results obtained, several conclusions were obtained from the analysis carried out. In January-April 2023 there were 637 traffic accidents in Sleman Regency, Yogyakarta. The highest number of accidents occurred at the beginning of the year, namely in January, while the lowest number of accidents occurred in March. Generally, accident victims suffer minor injuries. Victims aged 0-25 years are more often involved in accidents. Not having a driver's license is the highest number compared to people who have a driver's license. The number of accidents during busy times is higher than during quiet times. The male gender is more likely to experience traffic accidents than the female gender. The role of the victim who experiences accidents more often is the driver. The most frequently involved types of accidents were other accidents (side-by-side and pedestrian/cyclist). The profession of victims more often involved is students. The type of vehicle for both opponents and victims that is often involved is generally a motorbike. Based on the output from backward elimination, the factors that influence the severity of traffic accident victims in Sleman Regency in January-April 2023 are the opponent's vehicle factor for four/more wheeled vehicles, and the opponent's vehicle factor for non-motorized vehicles. It is hoped that local governments would be able to use the study's findings as a reference for determining what steps should be made to lower the frequency of traffic accidents.

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