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Original Article

Understanding Traffic Accident Patterns on the Jakarta-Cikampek Toll Road: An Integrated Approach Combining Blackspot Analysis and Human Factors

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Abstract

Traffic accidents on toll roads remain a major safety concern, particularly on high-traffic corridors such as the Jakarta-Cikampek Toll Road in Indonesia. This study aims to identify accident-prone locations (blackspots) and analyze contributing factors, with a focus on human-related aspects such as fatigue and rest adequacy. An integrated approach combining spatial analysis and multiple linear regression was employed to better understand accident patterns and their determinants. The study utilizes historical accident data from the Indonesian National Police Traffic Corps and toll road operators for the period 2021-2023, complemented by interview-based behavioral data. Blackspots were identified using a severity-based weighting method, while regression analysis examined the relationship between rest adequacy and variables such as gender, driving experience, travel characteristics, fatigue indicators, sleep duration, and risk perception. The results indicate that no variables are statistically significant at the 5 percent level. However, gender shows the strongest relationship with rest adequacy (β = -0.313; Sig. = 0.060), while sleep duration (β = 0.156) and risk perception (β = 0.102) exhibit positive tendencies. Fatigue indicators show mixed results, suggesting that fatigue is a complex and multidimensional factor. Spatial analysis also reveals several high-risk segments associated with traffic density and road conditions. These findings highlight the need for integrated safety strategies that address both location-based risks and human factors. The study contributes to evidence-based approaches for improving toll road safety.

Keywords: Blackspot, Human Factors, Regression Analysis, Toll Road Safety, Traffic Accidents.

1. Introduction

The Jakarta-Cikampek Toll Road is one of the toll road segments with the highest traffic volume in Indonesia. This road connects the economic center of Jakarta with surrounding areas such as Bekasi, Karawang, and Cikampek. Its strategic position makes the Jakarta-Cikampek Toll Road a primary corridor for the movement of people and goods between regions, making it highly vital in supporting national economic growth. However, the high traffic intensity also implies an increased risk to road safety along this corridor (Indonesia Ministry of Public Works and Housing, 2022).

The graph illustrates the development of accident numbers on the Jakarta-Cikampek Toll Road during the 2023-2025 period, categorized into four main indicators: total accidents, fatalities, serious injuries, and minor injuries.

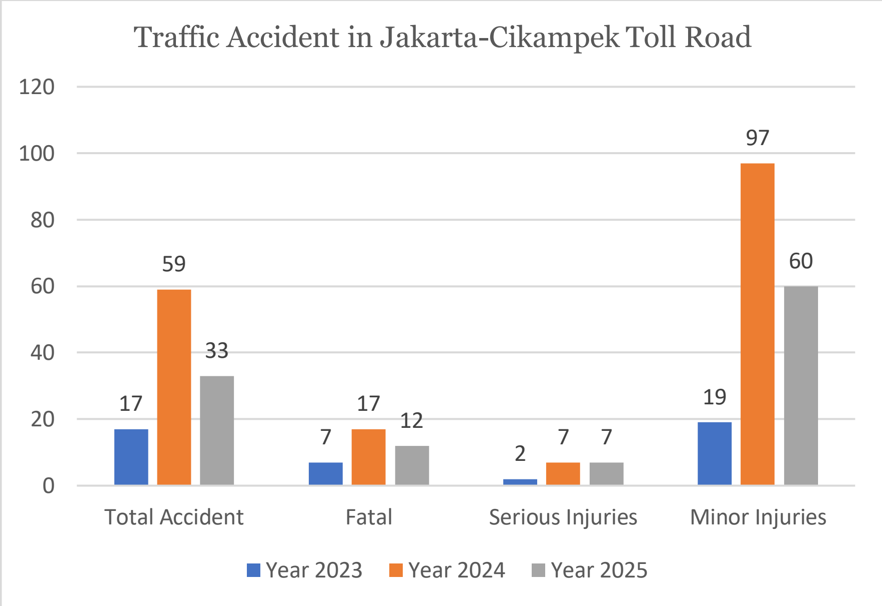

Figure 1. Traffic Accident in Jakarta-Cikampek Toll Road

In general, 2023 recorded the highest number of accidents compared to the other two years, particularly in the minor injury category, which reached nearly 100 cases. This indicates a significant increase in non-fatal accidents, which may be attributed to traffic congestion or driver-related factors such as fatigue and excessive speed.

Meanwhile, in 2024 there was a decrease across all categories, and this trend continued into 2025. Although the figures in 2025 are lower, they still highlight the need for sustained safety improvement efforts. This decline may indicate progress in safety measures, such as infrastructure improvements, increased enforcement, or road safety awareness campaigns.

The categories of fatalities and serious injuries are relatively lower compared to the total number of accidents, yet they still show fluctuations that require attention. Even small changes in fatality rates can have a significant impact on evaluating toll road safety performance.

From this graph, it can be concluded that 2023 represents a critical period in terms of safety on the Jakarta-Cikampek Toll Road. This finding can serve as a basis for further analysis of accident causation factors and for developing mitigation strategies in subsequent years, particularly in maintaining the declining trend observed through 2025.

Accidents occurring along this toll road are not only driven by high traffic volumes but also by various interrelated factors. Road user behavior, such as driving at high speeds or lack of attentiveness, is a major contributor to incidents in the field. In addition, road geometric conditions such as sharp curves, inadequate lighting, and limited safety facilities also increase the risk of accidents. (Indonesia Transportation Research and Development Agency, 2021)

The identification of accident-prone locations (blackspots) is a crucial initial step in efforts to reduce traffic accident rates, particularly on toll roads with high traffic volumes such as the Jakarta-Cikampek corridor. By accurately identifying locations with a high frequency of accidents, policymakers are able to implement more targeted and measurable interventions to improve road safety. As emphasized by Elvik (2008) and the Indonesian National Police Traffic Corps (*Korlantas Polri*, 2020), a blackspot-based approach serves as a fundamental component of sustainable road safety management.

In this study, the approach employed includes spatial analysis and statistical methods based on blackspot modeling to identify high-risk locations and analyze the key contributing factors of accidents along the Jakarta-Cikampek Toll Road. The results of this analysis are expected to provide strategic recommendations that support the formulation of accident risk mitigation policies, the improvement of driving safety, and the optimization of toll road infrastructure. Therefore, this scientific approach contributes to enhancing toll road safety in a sustainable and evidence-based manner.

2. Literature Review

2.1. Traffic Accidents

Traffic accidents represent one of the most serious transportation safety issues in many countries, including Indonesia. On high-intensity toll road corridors such as the Jakarta-Cikampek Toll Road, accidents are often influenced by a combination of human factors, road conditions, environmental aspects, and traffic characteristics. This phenomenon is consistent with the findings of Elvik (2024), which indicate that accidents on modern road infrastructure are rarely caused by a single factor, but rather result from complex interactions among driver behavior, geometric conditions, and traffic situations (Accident Analysis and Prevention).

Fundamentally, traffic accidents are unexpected events that occur on the road as a result of interactions among human, vehicle, road, and environmental factors. Tamin (2000) explains that accidents are consequences of complex transportation system interactions and are almost never triggered by a single cause. This aligns with the perspective of Elvik (2008; 2024), who emphasizes that accidents arise from a combination of human error, physical road conditions, traffic characteristics, and external factors such as weather.

Within the road safety system framework, human factors remain the dominant contributor to accident occurrence. A study by Madushani et al. (2023) shows that more than 70 percent of toll road accidents are influenced by driver behavior, including speeding, fatigue, and lack of alertness. Technical vehicle factors also contribute significantly, as demonstrated by Chen et al. (2021), who found that brake failure, tire conditions, and mechanical defects are major triggers of high-speed accidents. In addition, environmental aspects such as rain, fog, and low lighting have been proven to substantially increase accident risk (Gao et al., 2025). Warpani (2002) further emphasizes that pavement quality, gradients, curves, and the presence of road signs and markings play an important role in determining the likelihood of drivers losing control. Therefore, traffic accidents can be understood as a multidimensional phenomenon that occurs when disturbances in one element of the transportation system are not adequately mitigated, resulting in conflicts among vehicles, road users, and environmental conditions.

Traffic accidents on toll roads exhibit distinct characteristics compared to those on urban or arterial roads, due to the fundamental nature of toll roads being designed for high speeds, long-distance travel, and relatively homogeneous traffic flow. Ogden (1996) states that high speeds combined with monotonous driving conditions increase the risk of fatigue and reduced driver alertness, thereby raising the likelihood of both multiple-vehicle collisions and single-vehicle accidents. An international study by Karamanlis et al. (2023) also indicates that accidents on expressways tend to have higher fatality rates due to the greater impact energy associated with high-speed travel. Driver behavior factors such as unsafe overtaking, inadequate following distance, and visual distraction have been identified as significant contributors to accidents on toll roads (Khatun et al., 2024).

In addition to human factors, the physical characteristics of toll roads directly influence accident risk. Road gradients, sharp curves, geometric transitions, and pavement deterioration are commonly identified factors in accident analyses on expressways (Kumara & Walgampaya, 2021). Environmental conditions such as lighting and weather also play a major role. Research by Gao et al. (2025) shows that heavy rain, fog, and low lighting significantly increase accident risk by reducing visibility and tire-road friction. In Indonesia, the Indonesia Transportation Research and Development Agency (Puslitbang Transportasi, 2021) found that toll road accidents are generally caused by a combination of high speeds, driver fatigue, maneuvering errors, and technical vehicle failures such as brake or tire problems.

Overall, toll road accidents tend to involve high speeds, long and monotonous travel conditions, and vulnerability to environmental changes. This combination results in accident characteristics that are generally more severe, potentially fatal, and often concentrated in specific segments with geometric issues or high traffic density. Therefore, understanding the unique characteristics of toll road accidents is essential for formulating targeted prevention and mitigation strategies.

2.2. Blackspot in Traffic Accident

The blackspot method is an important approach in road safety analysis used to identify locations with a high concentration of traffic accidents within a specific period. Elvik (2015) explains that blackspots are determined through the analysis of historical accident data to identify points or road segments with accident rates exceeding statistically normal thresholds. This approach is also supported by PIARC (2013), which states that accident-prone locations are identified by comparing accident frequencies against predefined threshold values to ensure that such locations indeed exhibit higher risks than others.

In Indonesia, the definition of blackspots has been regulated in several technical guidelines issued by government agencies. According to the Guideline for the Handling of Accident-Prone Locations published by the Indonesia Ministry of Settlement and Regional Infrastructure, an accident-prone location is defined as a road segment or intersection of approximately 200-300 meters that exhibits similar accident causation factors within a specific spatial extent. Meanwhile, the Operational Guideline of ABIU/UPK issued by the Indonesia Ministry of Transportation (DepHub RI, 2007) expands this definition to include intersections, bridges, and short segments of less than 0.3 km that show high accident frequency, including incidents involving fatalities or significant losses exceeding a minimum annual threshold.

Furthermore, the Instruction of the Director General of Highways No. 02/IN/Db/2012 issued by the Indonesia Ministry of Public Works states that accident-prone locations are points or road segments characterized by high accident frequency and recurring incidents within a certain time period. This definition emphasizes that a blackspot is not merely a location where accidents have occurred, but rather a location that demonstrates a consistent pattern of repeated incidents, thereby requiring special attention in road safety management.

Thus, the blackspot method does not only serve to identify high-risk locations, but also provides a foundation for prioritizing road safety interventions. Through historical data-based analysis, government agencies and road operators can determine the most appropriate measures, ranging from traffic engineering improvements, enhancement of safety facilities, law enforcement, to educational campaigns aimed at reducing accident risks in critical locations. This approach plays a significant role in achieving a safer and more sustainable transportation system.

The blackspot identification method used by the Indonesian National Police Traffic Corps (Korlantas Polri) represents a practical and structured approach to identifying high-risk accident locations. In this guideline, blackspot determination is based on three main components: road segment boundaries, time period, and a value representing accident severity. The road segment boundary refers to the study length analyzed, typically ranging from 0 to 500 meters, ensuring that the assessment focuses on specific points or short segments with high accident intensity. The time boundary adopts a two-year period as a reference to determine whether a location consistently experiences significant accident occurrences.

The third component involves assessing accident severity using a weighting system. The Indonesian National Police Traffic Corps assigns weights based on accident impact including fatalities are assigned a weight of 10, serious injuries are assigned a weight of 5, and minor injuries are assigned a weight of 1. A location is classified as a blackspot if it reaches a minimum weighted score of 30 within one evaluation cycle. This weighting system allows for a more balanced analysis by considering not only accident frequency but also the severity of its impact on road users.

After identifying potential locations, the analysis proceeds with more detailed steps. The first stage involves understanding the blackspot concept, including definitions, handling procedures, and accident weighting calculations. In the blackspot determination stage, preliminary analyses are conducted, such as mapping locations using the Integrated Road Safety Management System (IRSMS), constructing collision diagrams and collision matrices, and developing accident sketches to understand the patterns occurring at the site. These steps help identify whether accidents share common characteristics, such as collision angles, vehicle directions, or specific conflict points.

The next stage is analysis and recommendation, which includes visual mapping of blackspots, data tabulation, cross-analysis to identify dominant accident characteristics, and the development of technical recommendations based on identified patterns. This stage is essential to ensure that the proposed solutions are targeted and effective, such as the installation of traffic signs, improvement of road markings, enhancement of lighting, modification of road geometry, or increased enforcement.

The final stage is reporting, which includes the formulation of design and safety facility issues, social analysis if necessary, and the preparation of final recommendations and a comprehensive blackspot handling report. This report serves as a basis for relevant agencies in determining policies and implementing corrective actions in the field. Through this systematic and data-driven approach, the blackspot method of the Indonesian National Police Traffic Corps becomes a key instrument in reducing accident rates and improving road safety in Indonesia.

2.3. Multiple Linear Regression

Multiple linear regression is a statistical method used to examine the relationship between one dependent variable and two or more independent variables, enabling researchers to assess the simultaneous influence of multiple factors on a particular phenomenon. According to Gujarati (2002) and Montgomery et al. (2021), this method is widely used to model linear relationships and identify the most significant contributing variables across various fields, including transportation safety. Mathematically, the model is expressed as $Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k + \varepsilon$, where $\beta_0$represents the intercept, $\beta_1, \ldots, \beta_k$are the regression coefficients indicating the direction and magnitude of each independent variable's effect, and $\varepsilon$is the error term.

The analytical process begins with model specification, where relevant variables are selected based on theoretical foundations and prior empirical studies, such as traffic volume, road geometry, environmental conditions, and driver behavior. The data are then prepared and, if necessary, transformed to meet analytical requirements before estimating the parameters using the Ordinary Least Squares (OLS) method. Prior to interpreting the results, classical assumption tests are conducted to ensure the validity of the model, including tests for normality of residuals, multicollinearity among independent variables, heteroskedasticity, and autocorrelation for time-series data. Only models that satisfy these assumptions are considered reliable for further analysis.

Subsequently, the model's goodness-of-fit is evaluated using statistical tests. The F-test is used to determine whether the independent variables collectively have a significant effect on the dependent variable, while the t-test assesses the significance of each variable individually. Additionally, the coefficient of determination (R^2) and adjusted R^2 are analyzed to measure how well the model explains the variation in the dependent variable. A higher R^2 value indicates stronger explanatory power. Finally, interpretation focuses on understanding the direction, magnitude, and statistical significance of each coefficient, while also relating the findings to real-world conditions and existing theories. This comprehensive interpretation allows the regression model to not only provide numerical results but also offer meaningful insights into the underlying patterns of traffic accidents.

2.4. Previous Research

Previous studies on traffic accident analysis, particularly on toll roads, have shown significant development in both methodological approaches and analytical depth. Many studies have focused on identifying accident-prone locations (blackspots) using spatial analysis techniques such as Geographic Information Systems (GIS) and Kernel Density Estimation. For instance, research by Khatun et al. (2024) demonstrated that GIS-based analysis is highly effective in mapping accident concentrations and visualizing high-risk zones. Similarly, Zhang et al. (2023) utilized spatial clustering methods to identify accident hotspots on expressways, highlighting the importance of geographical patterns in understanding accident distribution. These approaches provide strong visual and spatial insights, but often lack the ability to explain the underlying causal mechanisms driving accidents.

In addition to spatial approaches, several studies have employed statistical and machine learning methods to analyze accident causation factors. Kim et al. (2026) applied logistic regression to identify key predictors of toll road accidents, revealing that driver behavior such as speed, fatigue, and following distance plays a dominant role. Meanwhile, Newaz et al. (2026) used multivariate statistical models to examine the relationship between road geometry and accident frequency, confirming that curves, gradients, and lane configurations significantly influence accident risk. More advanced approaches, such as decision tree analysis (Abdullah & Sipos, 2023) and deep learning models (Karamanlis et al., 2023), have also been introduced to improve predictive accuracy and capture complex, nonlinear relationships among variables.

Despite these advancements, many studies tend to focus either on spatial identification of blackspots or on statistical analysis of accident factors separately. Spatial studies are effective in answering where accidents occur, while statistical models are useful in explaining why accidents happen. However, the lack of integration between these two approaches often limits the practical applicability of the findings, particularly in developing targeted and location-specific interventions. As a result, decision-makers may face challenges in prioritizing which locations require immediate attention based on both accident severity and contributing factors.

In the Indonesian context, research on toll road safety is still relatively limited and often relies on descriptive analysis or conventional weighting methods based on accident severity. Studies conducted by the Indonesia Transportation Research and Development Agency *(Puslitbang Transportasi)* and the Directorate General of Highways have identified accident-prone locations, but have not comprehensively analyzed the contribution of each causal factor using quantitative models. This indicates a gap in the application of integrated, data-driven approaches that combine spatial identification and statistical modeling to better understand accident dynamics.

Therefore, recent research trends emphasize the need for an integrated approach that combines blackspot identification with quantitative modeling techniques. By integrating spatial analysis and multiple linear regression, it becomes possible to not only identify high-risk locations but also quantify the influence of contributing factors such as traffic volume, road geometry, environmental conditions, and driver behavior. This integrated framework is expected to provide more robust, evidence-based insights for developing effective safety interventions and improving overall road safety performance.

3. Methods

3.1. Blackspot Location

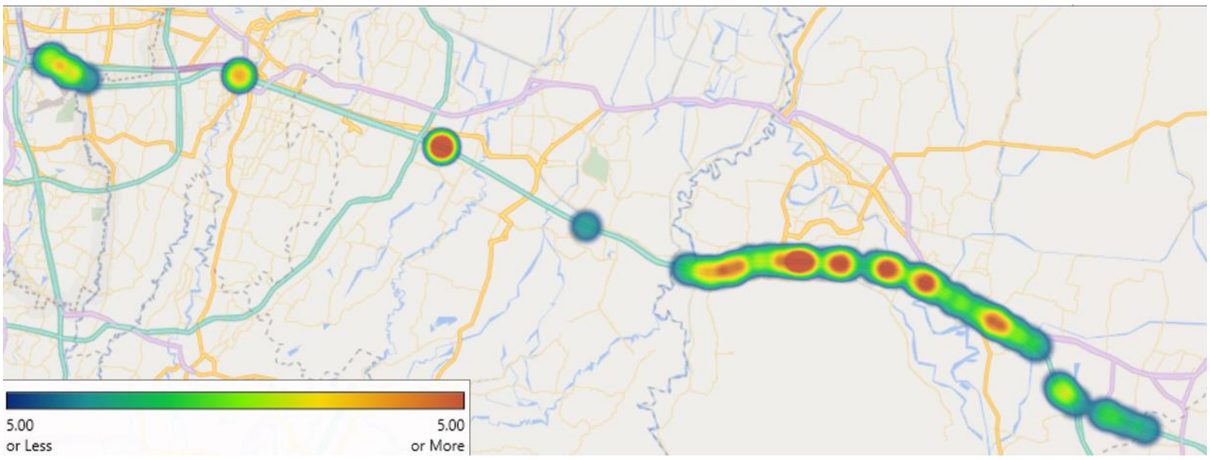

Figure 2. Blackspot Location

Figure 2 presents a heatmap illustrating the spatial distribution of accident incidents along the Jakarta-Cikampek Toll Road. In the context of traffic safety, this visualization can be interpreted as a preliminary indicator for identifying traffic accident blackspots, which are locations characterized by a high concentration of incidents occurring repeatedly over a certain period.

The heatmap is derived from historical accident data obtained from the Indonesian National Police Traffic Corps (*Korlantas Polri*) and toll road operators for the period 2021-2023, consistent with the dataset used in this study. The mapped variable represents accident frequency combined with severity-based weighting (fatalities = 10, serious injuries = 5, minor injuries = 1), following the blackspot identification method of the Indonesian National Police Traffic Corps. The spatial resolution is based on road segments of approximately 200-500 meters, as defined in the Indonesian Guideline for the Handling of Accident-Prone Locations.

Areas represented by yellow to red colors indicate higher intensity levels, suggesting a greater accumulation of traffic activity, violations, or potential vehicle conflicts compared to other areas. This pattern aligns with the concept of blackspots, where accidents are more likely to occur at locations with high interaction among road users, non-compliant driving behavior, and insufficient traffic control facilities. Therefore, points with higher intensity on the heatmap can be associated with locations that have a higher risk of traffic accidents.

Therefore, this heatmap can be utilized as an initial screening tool for identifying potential blackspots before conducting more detailed analyses using historical accident data.

The identified locations can serve as a basis for prioritizing safety interventions, such as improving the clarity of stop line markings, enhancing traffic control devices, and strengthening enforcement measures. Through this approach, traffic safety improvements can be implemented in a more targeted and data-driven manner.

3.2. Statistical Method

The variable coding process is a crucial step in transforming raw data into a structured format suitable for statistical analysis. In this study, the coding scheme was developed based on two primary data sources: official accident reports (Laporan Polisi/LP) obtained from the Indonesian National Police Traffic Corps (Korlantas Polri), and field-based insights collected through interviews with respondents and relevant stakeholders. These two sources were integrated to ensure that both quantitative accident data and qualitative behavioral aspects were adequately represented in the analysis.

The police reports provide detailed and objective information regarding accident characteristics, including time of occurrence, type of incident, and contributing factors identified at the scene. Meanwhile, the interview data complement this information by capturing subjective aspects such as driver fatigue, perception of risk, and behavioral tendencies that are not always fully recorded in official reports. This combination allows for a more comprehensive understanding of human factors influencing road safety, particularly in the context of toll road driving.

To enable the application of multiple linear regression analysis, all variables were systematically coded into numerical or categorical formats. Categorical variables such as gender, occupation, and trip purpose were transformed into numerical codes, while perceptual and behavioral variables, including fatigue indicators and risk perception, were measured using a Likert scale. Continuous variables such as travel duration and sleep duration were maintained in their original numerical form. This coding approach ensures consistency, comparability, and suitability of the dataset for statistical modeling.

The detailed coding scheme for all variables used in this study is presented in the following table 1.

Table 1. Statistic Coding Scheme

No	Variable Name	Variable Type	Description	Coding / Measurement
1.	Rest Adequacy	Dependent	Level of driver rest sufficiency	Scale / Index Score
2.	Year	Independent	Year of observation	Numeric (e.g., 2022-2025)
3.	Gender	Independent	Respondent gender	0 = Female; 1 = Male
4.	Occupation	Independent	Type of respondent occupation	1 = Student; 2 = Private; 3 = Government; 4 = Others
5.	Experience	Independent	Driving experience	1 = <1 year; 2 = 1-5 years; 3 = >5 years
6.	Trip Purpose	Independent	Purpose of travel	1 = Work; 2 = Leisure; 3 = Others
7.	Time	Independent	Time of travel	1 = Morning; 2 = Afternoon; 3 = Night
8.	Duration	Independent	Travel duration	Numeric (hours)
9.	In a Hurry	Independent	Urgency level while driving	Likert Scale (1-5)
10.	Fatigue 1	Independent	Feeling tired while driving	Likert Scale (1-5)

No	Variable Name	Variable Type	Description	Coding / Measurement
11.	Fatigue 2	Independent	Difficulty maintaining focus	Likert Scale (1-5)
12.	Fatigue 3	Independent	Feeling drowsy	Likert Scale (1-5)
13.	Fatigue 4	Independent	Frequent yawning	Likert Scale (1-5)
14.	Fatigue 5	Independent	Reduced alertness	Likert Scale (1-5)
15.	Fatigue 6	Independent	Physical exhaustion	Likert Scale (1-5)
16.	Fatigue 7	Independent	Microsleep tendency	Likert Scale (1-5)
17.	Sleep Duration	Independent	Duration of sleep before driving	Numeric (hours)
18.	Risk	Independent	Risk perception while driving	Likert Scale (1-5)
19.	Factor	Independent	Composite or external influencing factor	Index / Score

4. Results and Discussion

4.1. Multiple Linear Regression Analysis

Table 2. Statistical Result

Variables	B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part
(Constant)	5.020	1.544	-	3.251	.002	-	-	-
Year	-0.037	0.210	-0.028	-0.177	.860	-0.130	-0.028	-0.024
Gender	-0.669	0.346	-0.313	-1.936	.060	-0.267	-0.289	-0.264
Occupation	-0.142	0.126	-0.193	-1.126	.267	-0.177	-0.173	-0.153
Experience	-0.079	0.104	-0.116	-0.758	.453	-0.064	-0.118	-0.103
Trip Purpose	-0.100	0.156	-0.103	-0.644	.523	-0.086	-0.100	-0.088
Time	0.106	0.113	0.146	0.936	.355	0.175	0.145	0.128
Duration	-0.048	0.157	-0.049	-0.304	.763	-0.030	-0.047	-0.041
In a Hurry	-0.136	0.145	-0.154	-0.936	.355	-0.155	-0.145	-0.128
Fatigue 1	0.113	0.161	0.114	0.706	.484	0.112	0.110	0.096
Fatigue 2	-0.213	0.194	-0.166	-1.101	.277	-0.207	-0.169	-0.150
Fatigue 3	0.078	0.208	0.065	0.372	.711	-0.102	0.058	0.051
Fatigue 4	-0.097	0.196	-0.085	-0.494	.624	0.010	-0.077	-0.067
Fatigue 5	-0.048	0.192	-0.039	-0.250	.804	-0.004	-0.039	-0.034
Fatigue 6	0.043	0.199	0.038	0.215	.831	-0.130	0.034	0.029
Fatigue 7	-0.044	0.165	-0.043	-0.265	.792	-0.047	-0.041	-0.036
Sleep Duration	0.141	0.144	0.156	0.975	.335	0.121	0.151	0.133
Risk	0.133	0.201	0.102	0.660	.513	-0.032	0.103	0.090
Factor	-0.027	0.100	-0.042	-0.271	.787	0.071	-0.042	-0.037

The results of the multiple linear regression analysis indicate that, in general, the independent variables included in the model do not show a statistically significant effect on the dependent variable, namely rest adequacy. This is evidenced by the significance (Sig.) values of almost all variables, which exceed the threshold of $\alpha = 0.05$. Therefore, it can be concluded that, individually, none of the variables have a statistically significant influence on rest adequacy within the constructed model.

However, in terms of the direction of relationships, several variables exhibit notable tendencies. The gender variable shows a negative coefficient ($B = -0.669$; $\beta = -0.313$) with a significance value approaching the threshold (Sig. = 0.060), suggesting a potential difference in rest adequacy between gender groups, although this effect is not statistically significant. Meanwhile, variables such as risk perception (B = 0.133; β = 0.102) and sleep duration (B = 0.141; β = 0.156) demonstrate positive relationships, indicating that higher perceived risk and longer sleep duration tend to be associated with better rest adequacy, although these relationships remain statistically insignificant.

For the fatigue-related variables (Fatigue1 to Fatigue7), the results show mixed directions of influence, both positive and negative, but none of them reach statistical significance. This suggests that the fatigue indicators used in this study are not sufficiently strong to explain variations in rest adequacy within the regression model. Similarly, other variables such as year, occupation, experience, trip purpose, time, travel duration, and urgency (rushing) also do not contribute significantly, as reflected by their low t-values and high significance levels.

Overall, these findings indicate that the regression model has limited explanatory power in capturing the factors influencing rest adequacy. This may be attributed to several factors, including the possibility that the selected variables do not fully represent real-world conditions, the presence of other more dominant variables that were not included in the model, or the relatively homogeneous nature of the dataset. Therefore, further model development is recommended by incorporating additional relevant variables or applying alternative analytical approaches to obtain more robust and statistically significant results.

4.2. Interpretation

The results of the multiple linear regression analysis reveal that none of the independent variables included in the model exhibit a statistically significant effect on the dependent variable, namely rest adequacy, as indicated by significance values exceeding the threshold of $\alpha = 0.05$. At first glance, this suggests that the model is not sufficient to explain variations in rest adequacy among respondents. However, beyond statistical significance, the direction and magnitude of the regression coefficients still provide important insights into behavioral tendencies that are relevant to traffic safety analysis.

The gender variable shows a relatively strong negative standardized coefficient (β = -0.313) with a significance value approaching the threshold (Sig. = 0.060), indicating that gender differences may play a role in influencing rest adequacy, even though the relationship is not statistically significant at the conventional level. This finding suggests that certain demographic characteristics may influence fatigue patterns and rest behavior, which are critical factors in driving performance. Meanwhile, variables such as sleep duration (β = 0.156) and risk perception (β = 0.102) demonstrate positive relationships, implying that individuals who have longer sleep duration or higher awareness of risk tend to have better rest adequacy. Although these effects are not statistically significant, they align conceptually with established theories in traffic safety that emphasize the importance of adequate rest and risk awareness in reducing driver fatigue.

The fatigue-related variables (Fatigue1 to Fatigue7) show mixed coefficients, both positive and negative, indicating that the perception of fatigue is complex and not captured effectively through the selected indicators. The lack of statistical significance across these variables suggests that fatigue may not be adequately represented by self-reported measures alone, or that its impact is influenced by other latent factors such as driving environment, trip characteristics, or psychological conditions. Similarly, variables such as experience, occupation, trip purpose, travel time, travel duration, and urgency do not show significant contributions to rest adequacy, indicating that these factors may not directly influence rest conditions, or their effects are mediated by other variables not included in the model.

From the perspective of the research questions, particularly those related to identifying dominant human factors influencing driving conditions, these findings suggest that rest adequacy is not determined by a single observable variable, but rather by a complex interaction of behavioral, physiological, and situational factors. The absence of statistically significant variables does not necessarily imply the absence of relationships, but rather highlights the limitation of the current model in capturing the full complexity of driver fatigue and rest behavior. This finding reinforces the notion that human factors in traffic safety are inherently multidimensional and cannot be fully explained through simple linear relationships.

In the context of traffic safety, these results have important implications. Rest adequacy is closely related to driver fatigue, which is widely recognized as a major contributor to traffic accidents, particularly on toll roads characterized by long-distance travel and monotonous driving conditions. Even though the statistical model does not identify significant predictors, the observed tendencies suggest that inadequate rest, poor risk perception, and fatigue-related conditions still play a critical role in influencing driving performance. Drivers with insufficient rest are more likely to experience reduced alertness, slower reaction times, and increased likelihood of microsleep, all of which significantly increase the risk of accidents.

Therefore, the findings of this study highlight the need for a more comprehensive approach to analyzing human factors in traffic safety. Future research should consider incorporating additional variables such as physiological indicators, real-time driving behavior, and environmental conditions to better capture the dynamics of driver fatigue. From a practical standpoint, these results emphasize the importance of preventive measures such as promoting adequate rest, improving driver awareness, and providing sufficient rest area facilities along toll roads. In this regard, even in the absence of strong statistical significance, the study still contributes valuable insights into the relationship between human factors and traffic safety, supporting the development of more effective, evidence-based safety interventions.

5. Conclusion

This study aimed to examine the influence of demographic characteristics, travel attributes, fatigue indicators, and risk perception on rest adequacy as a proxy for driver condition related to traffic safety, while also identifying accident-prone locations (blackspots) along the Jakarta-Cikampek Toll Road using spatial analysis. Based on the multiple linear regression results, none of the independent variables show a statistically significant effect at the 5 percent level, as indicated by significance values greater than 0.05. For example, year (B = -0.037; Sig. = 0.860), occupation (B = -0.142; Sig. = 0.267), and experience (B = -0.079; Sig. = 0.453) demonstrate weak and insignificant relationships with rest adequacy.

However, several variables exhibit relatively stronger tendencies despite not reaching statistical significance. The gender variable shows the largest standardized coefficient (β = -0.313; B = -0.669; Sig. = 0.060), indicating a relatively stronger negative relationship compared to other variables and suggesting potential differences in rest adequacy across gender groups. In addition, sleep duration (B = 0.141; β = 0.156; Sig. = 0.335) and risk perception (B = 0.133; β = 0.102; Sig. = 0.513) show positive relationships, implying that increased sleep duration and higher awareness of risk tend to improve rest adequacy, although these effects remain statistically insignificant.

The fatigue-related variables (Fatigue1 to Fatigue7) show mixed results, with coefficients ranging from β = -0.166 (Fatigue2) to β = 0.114 (Fatigue1), and all significance values above

0.05. This indicates that the fatigue indicators used in this study are not strong predictors of rest adequacy within the current model. Similarly, variables such as time (B = 0.106; β = 0.146; Sig. = 0.355), duration (B = -0.048; Sig. = 0.763), and urgency (B = -0.136; Sig. = 0.355) also show weak and insignificant effects.

From a traffic safety perspective, these findings suggest that rest adequacy is influenced by a complex and multidimensional set of factors, rather than a single dominant variable. Although the regression results do not identify statistically significant predictors, the observed tendencies still align with established theories that highlight the importance of sleep duration, fatigue, and risk awareness in influencing driver performance. In the context of toll road driving, inadequate rest remains a critical concern, as it can lead to decreased alertness, slower reaction time, and increased likelihood of microsleep, all of which contribute to higher accident risk.

Overall, the results indicate that the current regression model has limited explanatory power in capturing the determinants of rest adequacy. This limitation may arise from unobserved variables or the complexity of human factors that are not fully represented in the model. Therefore, future research should incorporate additional variables, such as physiological indicators and real-time driving behavior, as well as alternative analytical approaches to better understand the relationship between driver condition and traffic safety. Despite the lack of statistical significance, this study provides important insights into the role of human factors in road safety and supports the need for preventive strategies focused on improving driver rest and awareness.

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