The Impact of Road Alignment Combinations on the Traffic Crash Rates on the Semarang-Solo Toll Road, Indonesia

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ABSTRACT

Road geometry is a crucial determinant of traffic safety, and combined horizontal–vertical alignments can substantially influence crash occurrence. This study investigates the effect of six alignment combinations: Straight–Flat, Straight–Uphill, Straight–Downhill, Curved–Level, Curved–Uphill, and Curved–Downhill, on crash frequency using data from the Semarang-Solo Toll Road, Indonesia. A total of 217 crash records (120 on Route A, 97 on Route B) were analyzed using chi-square tests, linear regression, and generalized linear models such as Poisson and Negative Binomial (NB). The Chi-square analysis revealed a significant association between alignment type and crash frequency ($\chi^2 = 28.45$, $p < 0.05$). Straight–Level segments recorded the highest crash share (47%), while Straight-Downhill and Straight-Uphill followed with 18.9% and 16.6%, respectively. Overdispersion (Pearson $\chi^2/df \approx 7.63$) justified the use of the NB model, which outperformed Poisson (AIC = 91.96 versus 104.54). Spatial analysis confirmed differing geometric risk patterns between routes, with Route A dominated by Straight–Flat crashes and Route B by Straight–Downhill. Furthermore, a multivariate analysis revealed that Straight–Flat segments were predominantly associated with rear-end collisions under clear weather (26.7%), while Straight–Downhill and Curved–Downhill sections exhibited elevated single-vehicle crash risks during rainfall. These findings indicate that crash occurrence is jointly influenced by geometric configuration and environmental conditions. These results demonstrate the influence of combined geometric configurations on crash frequency and provide empirical insights for improving design consistency and targeted countermeasures in Indonesian toll road networks.

Keywords-road alignment; crash frequency; negative binomial; chi-square test; spatial analysis; toll road

I. INTRODUCTION

Traffic crashes are a global public health concern and one of the leading causes of mortality and serious injury. According to the World Health Organization, more than 1.35 million lives are lost, and 20–50 million people are injured annually in road traffic incidents [1]. In Indonesia, the number of traffic crashes exceeds 100,000 cases each year, with more than 30,000 fatalities [2], reflecting persistent challenges in road safety management.

Traffic crashes are influenced by multiple factors, including human behavior, vehicle conditions, and roadway environment [3]. Among these, the roadway environment, particularly road geometry, plays a significant role in traffic safety [4, 5]. Road alignment, encompassing both horizontal (straight and curved) and vertical (flat, uphill, and downhill) components, affects drivers' visual demand, speed selection, and workload [6-8]. The interaction between horizontal and vertical alignments shapes roadway characteristics, which influence driver workload, behavior, and crash risk [8, 9].

The way road alignment influences crash occurrences has been explored. Authors in [6] highlighted that roadway geometry and environmental factors significantly affect crash frequencies on rural freeways. Authors in [10] reported spatial variations in crash rates across England and Wales linked to differences in roadway curvature, while authors in [11] found that in Malaysia, geometric design features influenced both the frequency and severity of head-on crashes. Authors in [12, 13] emphasized the role of consistent roadway alignment, developing indices and behavioral models to quantify roadside risk and speed behavior on two-lane rural roads.

More recent research has reinforced these findings, focusing on combined geometric effects. Authors in [14, 15] observed that rural segments combining sharp horizontal curves with steep vertical grades tend to experience higher crash risks due to limited sight distance. Authors in [16-18] confirmed that small curve radii and steep slopes significantly increase crash frequency, while authors in [19] demonstrated that geometric features, such as shoulder rumble strips, can mitigate such risks. Authors in [20] further demonstrated through Bayesian modeling that considering the integration of horizontal and vertical alignment improves crash prediction accuracy. Additionally, authors in [21, 22] highlighted the safety relevance of road width and vehicle type interactions in low-volume roads.

Most studies have analyzed horizontal or vertical alignments separately, or have been conducted on specific roadway segments in rural or international contexts [7, 23]. Comprehensive studies on the combined influence of horizontal and vertical alignments remain limited, particularly in the Indonesian toll road context [24]. Moreover, advanced modeling approaches, such as Bayesian hierarchical safety performance functions [25] and design consistency evaluations [26], have been applied internationally but are rarely used in Indonesia. Evaluating combined alignments is necessary to better explain roadway safety outcomes, especially in complex geometric environments [27]. Research has also explored the use of machine learning models to predict crash-prone areas based on geometric road features, identifying superelevation, entry speed, and sight distance as key predictors of crash risk [28].

However, most of these studies were conducted in developed or subtropical regions, under relatively homogeneous traffic and well-controlled design standards. In contrast, road systems in developing countries, such as Indonesia, feature mixed traffic, variable driver behavior, and inconsistent geometric transitions within short road segments. Hence, the combined effects of horizontal and vertical alignment under heterogeneous tropical conditions remain insufficiently explored. To address this gap, the present study provides a methodological and empirical contribution by simultaneously evaluating horizontal–vertical alignment interactions using a multi-model analytical framework integrating chi-square analysis, GLM Poisson/NB modeling, and spatial clustering.

This research evaluates the effects of integrated road alignments on crash frequency, focusing on six alignment combinations: Straight-Flat, Straight-Uphill, Straight-Downhill, Curved-Flat, Curved-Uphill, and Curved-Downhill. The analysis was conducted on two major routes, examining the distribution of crashes, testing the statistical relationship between alignment combinations and crash frequency, identifying dominant geometric factors influencing crashes, and performing spatial analysis by roadway segment. In addition, to achieve a more accurate evaluation of crash frequencies, the study uses Poisson models alongside the NB approach. The findings help develop road safety policies and improve geometric road design in Indonesia.

II. METHODOLOGY

A. Study Area

The study was conducted on Route A and Route B of the Semarang–Solo Toll Road, which features diverse combinations of vertical and horizontal alignments and a relatively high crash frequency compared to other toll corridors. The Semarang–Solo Toll Road is an inter-urban toll road, dual carriageway expressway located in Central Java. The corridor spans approximately 72.6 km, consisting of two and three lanes per direction with a median concrete barrier and guardrail for traffic control and safety.

B. Variable Data

To evaluate the correlation between road geometric characteristics and traffic crashes on the Semarang–Solo toll road, this study employs both independent and dependent variables, as presented in Table I. Vertical alignment was classified according to slope thresholds defined in the Bina Marga geometric design standard (2021). Segments were categorized as flat when the longitudinal gradient was less than 2%, uphill when the slope exceeded +2%, and downhill when the slope was below −2%. These threshold values were chosen to maintain consistency with national expressway design practices and to capture the operational distinctions perceived by drivers in real-world conditions.

TABLE I. RESEARCH VARIABLES

Variable type	Variable	Indicators
Independent variable	Road alignment combinations	Straight–Flat Straight–Uphill Straight–Downhill Curved–Flat Curved-Uphill Curved–Downhill
Dependent variable	Traffic crash frequency	Numerical count of crash events recorded for each alignment combination along Route A and Route B

Crest and sag vertical curves were not analyzed separately because detailed curve parameters, such as curve length, K-value, and vertical curvature radius, were unavailable in the toll operator's geometric dataset. A review of the as-built design drawings indicated that most vertical transitions along the Semarang–Solo Toll Road are gradual, resulting in negligible curvature effects on sight distance and vehicle dynamics. Therefore, the analysis focused on dominant combination gradient sections that better represent actual driving conditions along the corridor.

C. Data Source

The crash data were obtained from the official archives of tol authority, covering the 2021–2024 period [34]. The dataset includes variables for crash type, route segment, and geometric classification as maintained in the operator's design inventory. Direct measurements of traffic volume, surface friction, and lighting conditions were unavailable in the operator dataset.

Potential bias arising from secondary crash data was addressed by comparing crash type distributions with findings from comparable toll-road studies in Asia and the Middle East, which show similar dominance of rear-end and single-vehicle crashes (45–60%). This alignment supports the external consistency of the dataset. Nevertheless, the absence of direct measurements for traffic volume, skid resistance, and lighting is acknowledged as a limitation that may introduce residual bias despite internal cross-validation procedures.

D. Software and Analytical Tools

All statistical analyses were conducted using IBM SPSS Statistics 26. The chi-square, correlation, Poisson, NB, and regression analyses were performed in SPSS. Model validity was assessed using the Pearson χ^2/df ratio, Akaike Information Criterion (AIC), and residual diagnostics. Additional checks, including Variance Inflation Factor (VIF), were conducted to ensure the absence of multicollinearity and residual autocorrelation.

E. Geometry Classification Method

Road alignment categories were determined based on the combination of horizontal curvature and vertical gradient extracted from the official toll road operator's geometric design inventory. Six alignment categories were defined: Straight–Flat, Straight–Uphill, Straight–Downhill, Curved–Flat, Curved–Uphill, and Curved–Downhill.

F. Model Specification

The augmented NB model thus included: (1) categorical alignment combination (baseline = Straight–Flat), (2) ordinal curvature and gradient bins, (3) route fixed effect, and (4) log (L) as an exposure offset. Two-way interactions between curvature and grade were tested to capture combined geometric effects. Diagnostic tests confirmed no multicollinearity or autocorrelation after the inclusion of these quantitative variables.

G. Analysis of Data

The study employed a multi-stage workflow to quantify and interpret the relationship between road alignment combinations and crash frequency, while ensuring statistical validity.

1. Descriptive Analysis: first, crash counts and proportions were summarized by alignment combination and route to identify the distribution of crashes based on road alignment combinations and other crash characteristics.
2. Chi-square: The study tested whether there is a significant relationship between roadway alignment combinations and crash frequency. The hypotheses tested by the study are:

- H_0: No significant relationship exists between roadway alignment combinations and crash frequency.
- H_1: A significant relationship exists between roadway alignment combinations and crash frequency.

The chi-square formula used is:

$$\chi^2 = \sum \frac{(O-E)^2}{E} \tag{1}$$

where χ^2 is the chi-Square statistic value, O is the observed frequency from the data, and E is the expected frequency under the null hypothesis.

3. Correlation Analysis: Pearson (r) and Spearman (ρ) correlations were used, as appropriate, to examine monotonic relations between coded alignment indicators and crash counts, informing subsequent model specification.
4. Linear Regression: Analysis was applied to model how road alignment combinations influence crash frequency. The applied regression model is defined as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \tag{2}$$

where Y is the crash frequency, β_0 is the constant, β_1, β_2, …, β_n are the regression coefficients, X_1, X_2, …, X_n are independent variables, and ε is an error term.

Model validation and diagnostic tests were conducted to assess multicollinearity and residual independence.

5. Poisson and NB Regression

Because crashes are non-negative integers and often over-dispersed, a GLM framework with a log link was adopted. The Poisson and NB models were assessed using maximum likelihood under the GLM framework with a log-link function. Model goodness-of-fit was evaluated using AIC, log-likelihood, and Pearson χ^2/df.

1) Poisson Model

$$E[Y_i \mid X_i] =$$

$$\mu_i, \log(\mu_i) = \beta_0 + \beta^\top X_i + \log(\text{exposure}_i) \tag{3}$$

2) NB Model

The model to account for overdispersion is defined as [30]:

$$Var(Y_i) = \mu_i + \alpha\mu_i^2 \tag{4}$$

Overdispersion was evaluated using the Pearson χ^2/df ratio. Values much greater than 1 indicate Poisson misfit and justify the use of NB specification. Model selection relied on the AIC and log-likelihood comparison, while Incidence Rate Ratios (IRR = e^β) with 95% confidence intervals and p-values were reported for interpretability.

Each analytical method was selected to match the structure and characteristics of the data. The chi-square test was used to examine the independence between categorical variables. Correlation analysis was applied to identify the strength and direction of monotonic relationships among variables, supporting model specification. Linear regression served as an initial benchmark for descriptive association between alignment and crash frequency. Since crash data are count-based and over-dispersed, Poisson and NB models were employed under the generalized linear model framework. Finally, spatial analysis was integrated to visualize the spatial distribution of crashes, detect high-risk clusters, and complement statistical results with geographical patterns. The flow diagram of the research methodology is shown in Figure 1.

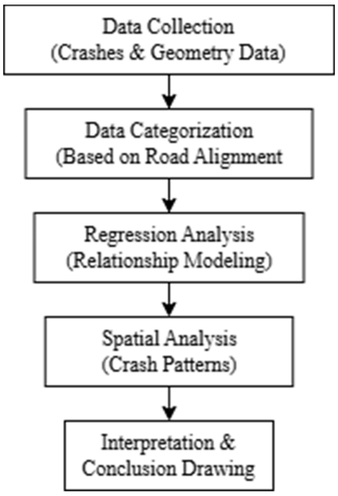

Fig. 1. Flow diagram of the research methodology.

Significance level was set at $\alpha = 0.05$. Robust standard errors were recommended if residual heterogeneity remained [16].

6. Spatial Analysis: Crash densities were mapped by alignment combination on Route A and Route B to identify clusters of high-risk segments. Spatial outputs were used to complement statistical findings rather than to infer causality.

III. RESULTS AND DISCUSSION

A. *Crash Distribution Based on Road Alignment Combinations*

A total of 217 crash records collected from official toll road operator archives covering the 2021–2024 period were analyzed. The record consists of 120 (55.3%) crashes on Route A and and 97 (44.7%) on Route B. Table II depicts the distribution of crashes based on road alignment combinations on both routes. It can be seen that the Straight–Flat alignment combination has the highest crash frequency (47.00%), followed by Straight–Downhill (18.89%) and Straight–Uphill (16.59%). Meanwhile, the Curved–Uphill and Curved–Downhill combinations share the same lowest crash frequency (4.15% each).

Differences in crash frequency may also reflect variations in segment length among alignment types. However, the available dataset did not include geometric inventory data specifying the total length of each alignment combination, so normalization of crash frequencies by segment length could not be performed.

Crash distribution patterns were largely similar across Route A and Route B, both dominated by Straight–Flat sections (54.17%) and Straight–Uphill (23.33%) combinations, whereas in Route B, the highest crash frequencies occurred on the Straight–Flat (38.14%) and Straight–Downhill (34.02%) combinations. This difference reflects the distinct geometric characteristics between the two routes, with Route B having a greater proportion of downhill sections compared to Route A.

TABLE II. DISTRIBUTION OF TRAFFIC CRASHES

No.	**Alignment combination**	**Route A**			**Route B**			**Total**		
		f	**% Route**	**% Total**	*f*	**% Route**	**% Total**	*f*	**% Total**	**Ranking**
1	Straight–Flat	65	54.17%	29.95%	37	38.14%	17.05%	102	47.00%	1
2	Straight–Uphill	28	23.33%	12.90%	8	8.25%	3.69%	36	16.59%	3
3	Straight–Downhill	8	6.67%	3.69%	33	34.02%	15.12%	41	18.89%	2
4	Curved–Flat	7	5.83%	3.23%	9	9.28%	4.15%	16	7.37%	4
5	Curved–Uphill	7	5.83%	3.23%	2	2.06%	0.92%	9	4.15%	5
6	Curved–Downhill	2	1.67%	0.92%	7	7.22%	3.23%	9	4.15%	5
7	Others*	3	2.50%	1.38%	1	1.03%	0.46%	4	1.84%	7
Total		120	100%	55.30%	97	100%	44.70%	217	100%	

*The category "Others" includes alignment combinations such as Flat–Straight, Uphill–Straight, and Downhill–Curved, which have a low frequency.

B. *Relationship Between Road Alignment Combinations and Crash Frequency*

1) *Contingency Evidence*

The chi-square test shows a statistically significant association between alignment categories and crash frequency across routes ($\chi^2 = 28.45$, $df = 6$, $p < 0.0001$), rejecting H_0 at $\alpha = 0.05$ and indicating that crash distributions differ across alignment combinations and routes:

$$\chi^2 = \frac{(65-56.41)^2}{56.41} + \frac{(37-45.59)^2}{45.59} + \ldots + \frac{(1-1.79)^2}{1.79}$$

$$\chi^2 = 1.31 + 1.62 + 3.29 + 4.07 + \ldots + 0.35$$

$$\chi^2 = 28.45$$

At 6 degrees of freedom, calculated as (7–1) × (2–1), and with a significance threshold of α = 0.05, the critical χ^2 value is determined to be 12.59. Since the calculated χ^2 value (28.45) > the critical value (12.59), H_0 is rejected. This result suggests a meaningful association between the categories of road alignment and the frequency of crashes.

The test statistic, χ^2 = 28.45 with 6 degrees of freedom, resulted in a p-value under 0.0001, thereby verifying the presence of a highly significant relationship. The chi-square results are presented in Table III.

2) Linear Regression Analysis

As a descriptive benchmark, the linear regression indicates that all alignment categories are associated with lower mean crash counts relative to the Straight–Flat reference; all coefficients are negative and statistically significant ($p < 0.05$), consistent with Table IV. From Table IV, it can be observed that all regression coefficients are negative and statistically significant ($p < 0.05$). This confirms that all road alignment combinations have significantly lower crash frequencies compared to the Straight–Flat combination (reference category). The determination coefficient (R^2) of 0.78 indicates that 78% of the variability in crash frequency can be explained by the road alignment combinations.

3) Poisson and NB Regression Analysis

Overdispersion check with Poisson is done as:

$$\frac{X^2}{df} = \frac{45.8}{6} \approx 7.63$$

Pearson $\chi^2/df \approx 7.63$ indicates strong overdispersion. This result suggests that the Poisson model is inadequate and supports the use of an NB regression model.

- Model Fit Comparison:

$$AIC\ (poisson) = -2 \times (-46.27) + 2 \times 6 = 104.54$$

$$AIC\ (nb) = -2 \times (37.98) + 2 \times 7 = 89.96$$

The Poisson model produced an AIC of approximately 104.54, while the NB model produced a lower AIC of approximately 91.96. This result suggests superior model fit for the NB model. The log-likelihood was –45.27 for the Poisson model and −37.98 for the NB model. This further confirms the superior fit of the NB model. Table V displays the results of the Poisson and NB regression models.

TABLE III. CHI-SQUARE TEST RESULTS

Road alignment combination	Route A (*O*)	Route A (*E*)	Route B (*O*)	Route B (*E*)	Total
Straight–Flat	65	56.41	37	45.59	102
Straight–Uphill	28	19.91	8	16.09	36
Straight–Downhill	8	22.67	33	18.33	41
Curved–Flat	7	8.85	9	7.15	16
Curved–Uphill	7	4.98	2	4.02	9
Curved–Downhill	2	4.98	7	4.02	9
Others	3	2.21	1	1.79	4
Total	120	120	97	97	217

TABLE IV. LINEAR REGRESSION ANALYSIS RESULTS

Variable	Coefficient (β)	Std. error	t-value	*p-value*
Constant	85.17	12.43	6.85	0.001
Straight–Uphill	-66	17.58	-3.75	0.013
Straight–Downhill	-61.17	17.58	-3.48	0.018
Curved–Flat	-86	17.58	-4.89	0.004
Curved–Uphill	-93	17.58	-5.29	0.003
Curved–Downhill	-93	17.58	-5.29	0.003

R^2 = 0.78; Adjusted R^2 = 0.65; F (5,6) = 4.31; p = 0.023

TABLE V. POISSON AND NB RESULTS

Covariate versus Straight-Flat	Poisson IRR (95% CI)	*p*	NB IRR (95% CI)	*p*
Route B (vs A)	0.82 (0.63–1.07)	0.151	0.93 (0.51–1.71)	0.821
Straight–Uphill	0.35 (0.24–0.52)	<0.001	0.35 (0.15–0.85)	0.02
Straight–Downhill	0.40 (0.28–0.58)	<0.001	0.41 (0.17 1.01)	0.052
Curved–Flat	0.16 (0.09–0.27)	<0.001	0.16 (0.06–0.41)	<0.001
Curved–Uphill	0.09 (0.05–0.17)	<0.001	0.09 (0.03–0.25)	<0.001
Curved–Downhill	0.09 (0.05–0.17)	<0.001	0.09 (0.03–0.26)	<0.001

Note: (IRR, baseline = Straight-Flat) Interpretation: IRR < 1 indicates fewer crashes than Straight-Flat.

As shown in Figure 2, the NB model provided a superior fit (AIC = 91.96 versus 104.54 for Poisson) and more stable IRR estimates, confirming that the NB specification adequately captured overdispersion in the data. Compared to the Straight–Flat baseline (IRR = 1.00), all other alignment combinations exhibited significantly lower crash frequencies (IRR range: 0.09–0.41, $p < 0.05$), except for Straight–Downhill, which was marginally significant (p = 0.052). The confidence intervals demonstrate that model uncertainty was within acceptable limits. No statistically significant differences were found between Route A and Route B after controlling for alignment. These findings indicate that simpler geometric configurations, particularly Straight–Flat segments, are associated with higher crash propensity.

The Generalized Linear Modeling (GLM) analysis of crash counts revealed strong evidence of overdispersion in the Poisson specification (Pearson χ^2/df = 7.63), indicating that the variance substantially exceeded the mean. Consequently, the NB model was adopted as a more appropriate count structure. The NB model achieved a markedly better fit, with lower (AIC = 91.96 versus 104.54 for Poisson) and higher log-likelihood (–37.98 versus –45.27), confirming its superiority in capturing data variability. The exponentiated coefficients (IRRs) demonstrated that, relative to the Straight–Flat baseline (IRR = 1.00), all other alignment combinations exhibited significantly lower crash frequencies (IRR range = 0.09–0.41, $p < 0.05$), except Straight–Downhill, which was marginally significant ($p = 0.052$).

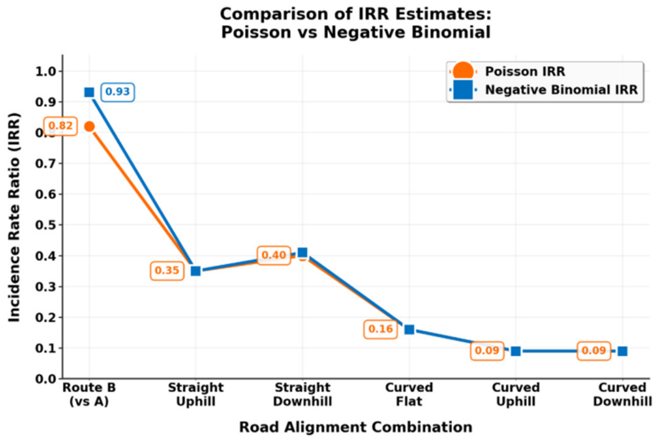

Fig. 2. Comparison of IRR estimates (Poisson versus NB) with 95% confidence intervals.

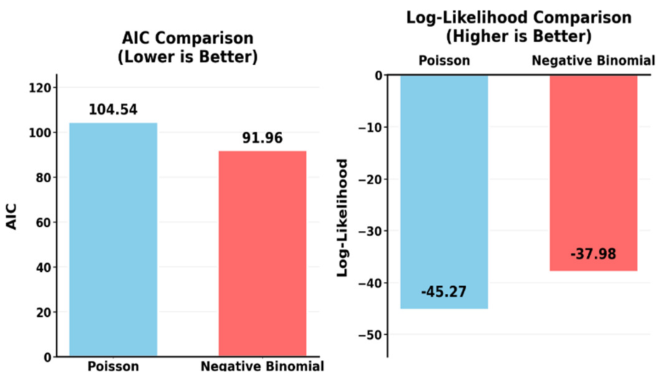

Fig. 3. Comparison of model fit based on AIC and log-likelihood.

The differences between Route A and Route B were statistically insignificant after adjusting for alignment, indicating that alignment type, rather than corridor location, primarily drives crash variability. Variance comparison further validated the NB model's suitability, as the observed variance-to-mean ratio greatly exceeded unity—a condition that the Poisson model could not accommodate. These findings align with those in [11, 29, 33], all of which observed elevated crash rates on flat and downhill segments, attributable to excessive speeds and reduced driver vigilance. Similarly, authors in [6, 20] confirmed that roadway geometric consistency significantly affects crash likelihood and that heterogeneous roadway geometries naturally produce over-dispersed crash data. More recent frameworks, such as [17, 34], also emphasized curvature and gradient as the dominant predictors of crash occurrence, consistent with the present study's empirical evidence.

4) Dominant Geometric Factors in Traffic Crashes

To identify the dominant geometric factors in crashes, a factor analysis was conducted on the road alignment combination data. The results indicate that two main factors contribute to crashes:

- Horizontal Alignment Factor (Straight/Curved): Differentiates between straight and curved roads. Straight roads account for a much higher crash frequency (82.48%) compared to curved roads (15.67%).
- Vertical Alignment Factor (Flat/Uphill/Downhill): This factor differentiates between flat, uphill, and downhill roads. Flat roads record the highest crash frequency (54.37%), followed by downhill (23.04%) and uphill roads (20.74%).

The interaction between these two factors shows that the Straight–Flat combination is the most dominant road geometry in crash occurrences, despite being theoretically less complex. This can be explained through further analysis of driver behavior and traffic characteristics within each alignment combination.

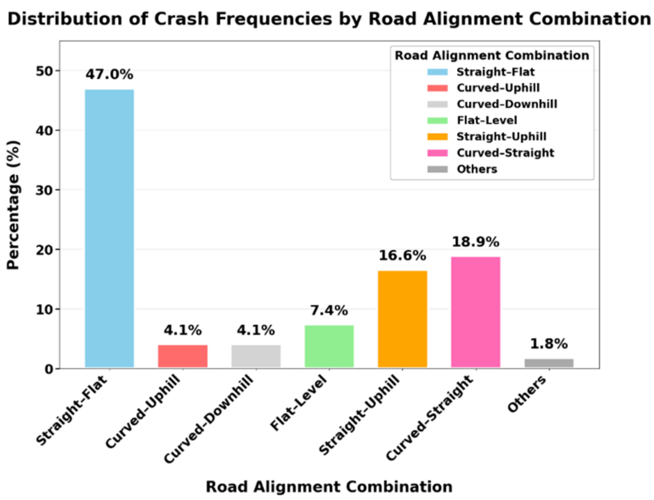

Fig. 4. Distribution of crash frequencies by road alignment combination.

The distribution of crashes across alignment combinations showed that Straight–Flat segments recorded the highest proportion of total crashes (47%), followed by Straight–Downhill (18.9%) and Straight–Uphill (16.6%). Curved–Flat, Curved–Uphill, and Curved–Downhill segments accounted for 7.4%, 4.1%, and 4.1% of crashes, respectively. These proportions were consistent across both Route A and Route B, with minimal variation (standard deviation < 2%). Further analysis of the crash types within each alignment combination revealed distinct patterns. On Straight–Flat sections, rear-end collisions dominated (56.86%), while Curved–Downhill segments were primarily associated with single-vehicle crashes (44.44%). This indicates that the alignment configuration not only affects crash frequency but also the type of crash that tends to occur. Overall, the concentration of crashes on Straight–Flat and Straight–Downhill alignments supports the hypothesis that high operating speeds and reduced driver vigilance in simpler geometric environments increase crash risk

5) Spatial Analysis of Crashes and Road Geometry

A spatial analysis was conducted to identify the distribution patterns of crashes along each road segment and their relationship with road alignment combinations. Figure 5 illustrates the distribution of crashes on the segments with the highest crash frequencies in Route A and Route B.

a) Route A

The dominance of rear-end collisions in Straight–Flat sections (56.86% of all crashes in this alignment category) may reflect behavioral tendencies associated with higher operating speeds and closer following distances. On straight, level toll road segments with minimal geometric complexity, drivers tend to operate at speeds approaching or exceeding design limits while maintaining inadequate inter-vehicular spacing, creating conditions conducive to rear-end crashes when lead vehicles decelerate unexpectedly [6, 11]. This pattern is consistent with previous studies on toll roads and freeway safety, which identified excessive speeds on flat, straight alignments as a primary contributing factor to elevated crash rates [31-33].

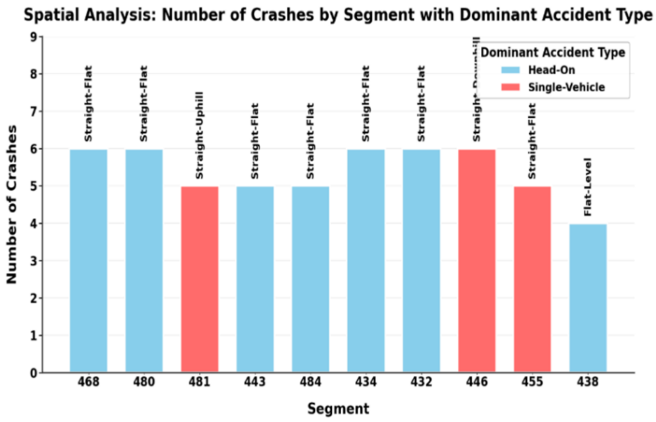

Fig. 5. Crash distribution on segments with the highest crash frequencies on Route A and Route B.

Across the dataset, Straight–Uphill alignments exhibited a significantly higher proportion of single-vehicle crashes compared to Straight–Flat sections (32.4% vs. 18.7%, χ^2 = 11.64, p<0.001). This pattern reflects multiple interrelated crash mechanisms associated with uphill gradients:

- Vehicle dynamics and performance limitations: On uphill grades, particularly those exceeding 3%, heavy vehicles experience reduced acceleration capability and speed decay, creating speed differentials with passenger vehicles and increasing the risk of loss-of-control incidents when drivers attempt to maintain speed [6, 7].
- Driver workload and fatigue: Uphill driving increases cognitive workload due to continuous throttle adjustment and gear changes, reducing attentional resources available for hazard detection and contributing to delayed reaction times [33].
- Geometric factors: Uphill sections often coincide with reduced sight distances due to vertical crest curves, limiting preview time for potential hazards and contributing to run-off-road and fixed-object collision risks.

This multi-factorial mechanism was evident across 12 uphill segments in the study corridor, with the effect most pronounced on grades >3% (38.6% single-vehicle crashes) compared to grades 2-3% (28.1%, p=0.023). These findings align with previous research demonstrating that longitudinal grades systematically alter vehicle dynamics, driver behavior, and crash patterns on high-speed facilities [6, 7, 33].

b) Route B

The crash pattern in Route B shows more varied alignment combinations. Segments 424 and 455 are dominated by the Straight–Downhill alignment, segments 432 and 446 by Straight–Flat, and segment 438 by Straight–Uphill. An interesting case is segment 455, where most crashes were single-vehicle crashes on a downhill straight road, indicating loss of control as a major factor. Conversely, segment 424, also Straight–Downhill, was dominated by rear-end collisions, implying that traffic volume or road conditions likely influence crash types.

6) Multivariate Analysis Alignment Combination, Crash Type, and Weather Condition

To gain a greater understanding of how geometric and environmental factors jointly affect crash occurrence, a multivariate cross-tabulation was conducted linking road alignment combinations, crash types, and weather conditions. The chi-square test of independence yielded a statistically significant association between the three variables (χ^2 = 42.73, df = 10, p < 0.001), indicating that crash type distributions vary systematically across alignment categories and weather conditions. The results of this analysis are presented in Table VI.

The Straight–Flat combination with rear-end collisions under clear weather conditions recorded the highest frequency (26.73%). This indicates that on straight and flat roads with favorable weather, drivers are inclined to operate at higher speeds while failing to preserve sufficient spacing between vehicles. The Straight–Downhill combination with single-vehicle crashes under rainy conditions accounts for a relatively high percentage (6.91%) compared to the overall frequency of the Straight–Downhill category. This suggests that downhill roads pose a particularly high risk during rainy weather, especially for single-vehicle crashes. For the Curved–Downhill combination, the proportion of single-vehicle crashes under rainy conditions is also relatively high. This emphasizes that the interaction of curves and downhill alignments becomes highly hazardous during adverse weather conditions.

TABLE VI. MULTIVARIATE ANALYSIS OF ROAD ALIGNMENT COMBINATIONS, ACCIDENT TYPES, AND WEATHER CONDITIONS

Alignment combination	Rear-end		Single-vehicle		Total crashes	Percentage (%)	Rank
	Clear	Rain	Clear	Rain			
Straight–Flat	58	0	33	0	102	47.00%	1
Straight–Downhill	17	0	0	15	47	21.70%	2
Straight–Uphill	21	0	10	0	31	14.30%	3
Curved–Flat	9	0	7	0	16	7.40%	4
Curved–Downhill	3	0	5	0	13	6.00%	5
Curved–Uphill	5	0	0	3	8	3.70%	6
Total	113	0	55	18	217	100%	

This multivariate analysis provides a deeper understanding of the interaction between road alignment combinations, crash types, and weather conditions. Such insights are highly valuable for designing more effective crash prevention strategies.

CONCLUSION

This study demonstrates that road alignment combinations significantly influence traffic crash frequency, with geometric design emerging as a critical safety determinant. Straight–Flat alignments exhibited the highest crash frequency, challenging assumptions that complex geometries pose greater risks. Horizontal alignment was identified as the dominant factor, while spatial analysis revealed high-risk clusters along specific segments. The novelty of this research lies in its holistic approach, integrating multiple statistical methods, such as chi-square, Poisson, and Negative Binomial (NB) regression, with spatial analysis to capture both statistical associations and geographical crash patterns. Unlike prior studies examining alignments separately or focusing on rural roads, this research provides context-specific evidence from Indonesian toll roads, advancing methodological approaches while offering practical insights for policymakers and infrastructure developers. Descriptive analysis yielded directional trends consistent with Poisson and NB models, confirming statistical reliability. Practically, the findings underscore the importance of geometric consistency and driver visibility in toll road design. Segments with Straight–Flat and Straight–Downhill configurations require enhanced signage, lane delineation, drainage, and gradient transition warnings. Design consistency checks should be institutionalized during alignment design and safety audit stages for early risk mitigation.

Future research should integrate additional explanatory variables, including traffic flow, vehicle composition, pavement condition, and lighting environment, to reduce omitted-variable bias. Advanced analytical frameworks, such as Bayesian hierarchical models, Generalized Additive Models (GAM), and machine-learning-based crash prediction, may improve predictive accuracy and reveal nonlinear geometry-crash relationships. Extending this framework to different toll networks or multi-year datasets would validate the robustness of geometric risk patterns identified in the present study.

REFERENCES

[1] World Health Organization, *Global Status Report on Road Safety 2018*. Geneva, Switzerland: World Health Organization, 2019.

[2] P. Lumba, A. Ariyanto, and A. Fathoni, "Strategies to Reduce the Number of Severely Injured Victims in Adolescent Motorcycle Riders," *IIUM Engineering Journal*, vol. 25, no. 1, pp. 153–166, Jan. 2024, https://doi.org/10.31436/iiumej.v25i1.2997.

[3] S. Saha and Z. Rehena, "Profiling the Causes of Vehicle Accidents to Prevent its Occurrence," in *2023 IEEE Silchar Subsection Conference (SILCON)*, Silchar, India, Nov. 2023, pp. 1–6, https://doi.org/10.1109/SILCON59133.2023.10405281.

[4] M. M. Nassef, "Road Safety Requirements," *International Journal of BIM and Engineering Science*, vol. 5, no. 2, pp. 66–73, 2022, https://doi.org/10.54216/IJBES.050205.

[5] A. Suraji and A. T. Mulyono, "Accident Risk Analysis of Road Geometric Components Using Functional Worthiness Approach," *Eastern-European Journal of Enterprise Technologies*, vol. 3, no. 1 (117), pp. 6–14, June 2022, https://doi.org/10.15587/1729-4061.2022.257977.

[6] V. Shankar, F. Mannering, and W. Barfield, "Effect of Roadway Geometrics and Environmental Factors on Rural Freeway Accident Frequencies," *Accident Analysis & Prevention*, vol. 27, no. 3, pp. 371–389, June 1995, https://doi.org/10.1016/0001-4575(94)00078-Z.

[7] L. Wang, "Safety Evaluation for Highway Geometric Design Based on Spatial Path Properties," *Journal of Advanced Transportation*, vol. 2023, pp. 1–14, Sept. 2023, https://doi.org/10.1155/2023/6685010.

[8] Y. Liang *et al.*, "Nonlinear Effects of Traffic Statuses and Road Geometries on Highway Traffic Accident Severity: A Machine Learning Approach," *PLOS ONE*, vol. 19, no. 11, Nov. 2024, Art. no. e0314133, https://doi.org/10.1371/journal.pone.0314133.

[9] N. Hang, Z. Xiang-mo, N. Chun-li, Y. Lan, and L. Jing, "Accident-Prone Section Prediction Models for Intelligent Vehicles Based on Road Alignment," *Zhongguo Gonglu Xuebao/China Journal of Highway and Transport*, vol. 34, no. 3, pp. 183–192, 2021.

[10] R. Haynes, A. Jones, V. Kennedy, I. Harvey, and T. Jewell, "District Variations in Road Curvature in England and Wales and their Association with Road-Traffic Crashes," *Environment and Planning A: Economy and Space*, vol. 39, no. 5, pp. 1222–1237, May 2007, https://doi.org/10.1068/a38106.

[11] M. Hosseinpour, A. S. Yahaya, and A. F. Sadullah, "Exploring the Effects of Roadway Characteristics on the Frequency and Severity of Head-on Crashes: Case Studies from Malaysian Federal Roads," *Accident Analysis & Prevention*, vol. 62, pp. 209–222, Jan. 2014, https://doi.org/10.1016/j.aap.2013.10.001.

[12] J. M. Pardillo-Mayora, C. A. Domínguez-Lira, and R. Jurado-Piña, "Empirical Calibration of a Roadside Hazardousness Index for Spanish Two-Lane Rural Roads," *Accident Analysis & Prevention*, vol. 42, no. 6, pp. 2018–2023, Nov. 2010, https://doi.org/10.1016/j.aap.2010.06.012.

[13] F. G. Praticò and M. Giunta, "Modeling Operating Speed of Two Lane Rural Roads," *Procedia - Social and Behavioral Sciences*, vol. 53, pp. 664–671, Oct. 2012, https://doi.org/10.1016/j.sbspro.2012.09.916.

[14] K. M. Bauer and D. W. Harwood, "Safety Effects of Horizontal Curve and Grade Combinations on Rural Two-Lane Highways," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2398, no. 1, pp. 37–49, Jan. 2013, https://doi.org/10.3141/2398-05.

[15] A. Shalkamy, K. El-Basyouny, and Y. Li, "Calibrating Safety-Based Design Charts for Horizontal Curves Using System Reliability Analysis and Multivariate Models," *Journal of Transportation Safety & Security*, vol. 14, no. 12, pp. 1997–2028, Dec. 2022, https://doi.org/10.1080/19439962.2021.1992552.

[16] M. Ghorbani, M. Saffarzadeh, and A. Naderan, "Crash Prediction Modeling for Horizontal Curves on Two-Lane, Two-Way Rural Highways Based on Consistency and Self-Explaining Characteristics Using Zero-Truncated Data," *KSCE Journal of Civil Engineering*, vol. 27, no. 8, pp. 3567–3580, Aug. 2023, https://doi.org/10.1007/s12205-023-0501-6.

[17] Y. Chen, C. Wang, and Y. Xie, "Modeling the Risk of Single-Vehicle Run-Off-Road Crashes on Horizontal Curves Using Connected Vehicle Data," *Analytic Methods in Accident Research*, vol. 43, Sept. 2024, Art. no. 100333, https://doi.org/10.1016/j.amar.2024.100333.

[18] S. Chen, T. U. Saeed, and S. Labi, "Impact of Road-Surface Condition on Rural Highway Safety: A Multivariate Random Parameters Negative Binomial Approach," *Analytic Methods in Accident Research*, vol. 16, pp. 75–89, Dec. 2017, https://doi.org/10.1016/j.amar.2017.09.001.

[19] K.-F. Wu, E. T. Donnell, and J. Aguero-Valverde, "Relating Crash Frequency and Severity: Evaluating the Effectiveness of Shoulder Rumble Strips on Reducing Fatal and Major Injury Crashes," *Accident Analysis & Prevention*, vol. 67, pp. 86–95, June 2014, https://doi.org/10.1016/j.aap.2014.02.004.

[20] C. Carrodano, "Data-Driven Risk Analysis of Nonlinear Factor Interactions in Road Safety Using Bayesian Networks," *Scientific Reports*, vol. 14, no. 1, Aug. 2024, Art. no. 18948, https://doi.org/10.1038/s41598-024-69740-6.

[21] C. V. Zegeer, R. Stewart, and F. Council, "Roadway Widths for Low-Traffic-Volume Roads," National Cooperative Highway Research Program, Report 362, Washington DC, USA, 1994.

[22] X. Zhu and S. Srinivasan, "A Comprehensive Analysis of Factors Influencing the Injury Severity of Large-Truck Crashes," *Accident Analysis & Prevention*, vol. 43, no. 1, pp. 49–57, Jan. 2011, https://doi.org/10.1016/j.aap.2010.07.007.

[23] M. B. Sushma and A. Maji, "A Modified Motion Planning Algorithm for Horizontal Highway Alignment Development," *Computer-Aided Civil and Infrastructure Engineering*, vol. 35, no. 8, pp. 818–831, Aug. 2020, https://doi.org/10.1111/mice.12534.

[24] A. K. Chhotu and S. K. Suman, "Predicting the Severity of Accidents at Highway Railway Level Crossings of the Eastern Zone of Indian Railways using Logistic Regression and Artificial Neural Network Models," *Engineering, Technology & Applied Science Research*, vol. 14, no. 3, pp. 14028–14032, June 2024, https://doi.org/10.48084/etasr.7011.

[25] M. Ahmed, H. Huang, M. Abdel-Aty, and B. Guevara, "Exploring a Bayesian Hierarchical Approach for Developing Safety Performance Functions for a Mountainous Freeway," *Accident Analysis & Prevention*, vol. 43, no. 4, pp. 1581–1589, July 2011, https://doi.org/10.1016/j.aap.2011.03.021.

[26] Y. Hassan, T. Sayed, and V. Tabernero, "Establishing Practical Approach for Design Consistency Evaluation," *Journal of Transportation Engineering*, vol. 127, no. 4, pp. 295–302, Aug. 2001, https://doi.org/10.1061/(ASCE)0733-947X(2001)127:4(295).

[27] X. Wang, S. Li, T. Shen, Y. Wang, W. Qi, and J. Yao, "The Impact of the Combination Equilibrium of Horizontal and Sag-Vertical Curves on Safety," *International Journal of Transportation Science and Technology*, vol. 12, no. 4, pp. 1006–1016, Dec. 2023, https://doi.org/10.1016/j.ijtst.2022.11.003.

[28] R. Mudiyono, J. Andry, and N. U. Azizah, "The Volumetric Properties Modified Asphalt Concrete Wearing Course with the Addition of Epoxy Resin and Steel Fiber for Road Pavement," *Civil Engineering and Architecture*, vol. 12, no. 4, pp. 3013–3023, July 2024, https://doi.org/10.13189/cea.2024.120438.

[29] J. M. Hilbe, *Negative Binomial Regression*, 2nd ed. Cambridge, England, UK: Cambridge University Press, 2011.

[30] A. C. Cameron and P. K. Trivedi, *Regression Analysis of Count Data*, 2nd ed. Cambridge, England, UK: Cambridge University Press, 2013.

[31] D. Lord and F. Mannering, "The Statistical Analysis of Crash-Frequency Data: A Review and Assessment of Methodological Alternatives," *Transportation Research Part A: Policy and Practice*, vol. 44, no. 5, pp. 291–305, June 2010, https://doi.org/10.1016/j.tra.2010.02.001.

[32] S. Washington, M. Karlaftis, F. Mannering, and P. Anastasopoulos, *Statistical and Econometric Methods for Transportation Data Analysis*, 3rd ed. London, UK: Chapman and Hall/CRC, 2020.

[33] M. Azhdari, A. T. Kashani, S. Amirifar, A. Taheri, and G. Müller, "Capturing Road-Level Heterogeneity in Crash Severity on Two-Lane Rural Highways: A Multilevel Mixed-Effects Approach." arXiv, 2025, https://doi.org/10.48550/ARXIV.2508.09941.

[34] PT Jasa Marga (Persero) Tbk, *"Traffic accident records for Semarang-Solo toll road 2021-2024-Internal Crashes Database,"* Jakarta, Indonesia: Toll Road Authority, 2024.