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Research Paper

Development of a Safety Indicator Model Using Braking Behavior at Urban Signalized Four-Leg Intersections

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Abstract

With the growth of the urban population and the resulting increase in the number of vehicles, ensuring safety on urban roads has become inevitable. In this context, the safety assessment of signalized intersections—due to their significant traffic and safety advantages—has become a common approach in traffic management. Signalized intersections are considered critical components of urban service systems. As urban traffic volumes increase, the number of trips rises accordingly, leading to a higher likelihood of conflicts and crashes. This study investigates the geometric and traffic-related factors influencing the frequency of hard braking events at urban signalized intersections, aiming to provide a framework for evaluating the safety index of such locations. This study analyzes the geometric and traffic characteristics of seven urban signalized intersections. Using aerial videography at each site and processing the footage through image analysis software, the number of critical conflicts—based on the hard braking conflict index—was determined. A total of 92,586 conflict events related to this safety index were examined. The statistical analysis was performed using a multiple linear regression model. The results indicate that an increase of one unit in traffic volume leads to a 0.6% rise in critical conflicts based on the hard braking index. Furthermore, a one km/h increase in average exit speed from intersections is associated with approximately a 3% increase in critical conflict frequency.

Keywords: Safety Four-Leg Signalized Intersections, Hard Braking, Performance Analysis, Image Processing, Traffic Conflicts

1. Introduction

Signalized intersections constitute critical components of urban transportation systems, exerting a direct influence on the overall efficiency and operational performance of roadway networks. Given that more than half of intra-city trips involve passage through these intersections, ensuring their safety and functionality is of paramount importance (Zheng et al., 2014). In the past decade, significant advancements have been made in the recording and analysis of conflicts at signalized intersections, leading to the development of new performance metrics (Day et al., 2014, Li et al., 2020a). These metrics now enable precise assessments of red-light violations, traffic flow quality, and queue conditions, thereby facilitating a more effective and comprehensive analysis of traffic behavior (Lavrenz et al., 2016, Chen et al., 2017). Transportation agencies typically assess the safety of intersections by analyzing crash data from the past 3 to 5 years (Golembiewski and Chandler, 2011). This traditional approach allows agencies to identify high-risk locations and develop appropriate safety programs. However, due to the reliance on historical data and the low crash rates in many areas, coupled with the necessity of multi-year data analysis for statistical modeling, this approach may lead to delays in implementing safety measures. Consequently, the transportation industry has turned to alternative indicators and real-time analysis to enhance the responsiveness and effectiveness of safety interventions. Since the 1960s, researchers have been exploring alternatives to, or supplements for, crash statistics by examining traffic conflicts(Wang et al., 2022). Traffic conflicts, which result from factors similar to those of crashes, are considered a better metric for identifying high-risk locations due to their higher frequency (Tarko, 2021). Over the past six decades, extensive research has been conducted to provide alternative or supplementary metrics to the sole use of crash statistics. The main objective of these efforts has been to develop methods that reduce the time required for data collection and improve the accuracy of traffic safety assessments (Arun et al., 2021, Tarko, 2018). In general, it can be said that traffic indicators showing conflicts can serve as an alternative to crash statistics, and these indicators can assist in identifying accident-prone locations(Ghanim et al., 2020, Yamada and Kuroki, 2019). several important traffic indicators used as alternatives to crash statistics include time-to-collision(Nadimi et al., 2020, Hayward, 1972), post-encroachment time (Allen et al., 1978, Peesapati et al., 2013) , and maximum deceleration rate to avoid a collision. The values of traffic indicators can be obtained manually, through simulation, video recording followed by analysis, or via sensors installed at the site or within the vehicle (Vajpayee et al., 2024).

2. Literature Review

Initially, when traffic indicators were being examined and introduced, the hard braking indicator was defined as one that analyzes any sudden driver action, such as hard braking, abrupt lane changes, or evasive maneuvers to avoid a collision (Older and Spicer, 1976). Despite the extensive research conducted on other indicators, the hard braking indicator has received comparatively less attention. Bagdadi introduced the Critical Jerking Method to distinguish between highly dangerous events and those with the potential to become critical (Bagdadi and Várhelyi, 2013). Hard braking has previously been recognized as a valid and alternative traffic conflict indicator for evaluating traffic safety, and it can reflect hazardous situations or emergency conditions (Mousavi, 2015, Guido et al., 2011). Desai et al. found in their research that the occurrence of hard braking (HB) conflicts, detected through vehicle-based methods, is significantly associated with crash frequency in urban areas. Their analysis demonstrated that hard braking is directly related to hazardous traffic conditions (Desai et al., 2021). Hunter et al., by analyzing 4.5 years of crash data and comparing it with one month of hard braking (HB) data, found a strong correlation between the HB indicator and rear-end collisions—particularly when hard braking occurs farther from the stop line. Statistical modeling results indicated that an increase in the number of hard braking events and traffic volume significantly raises the likelihood of crashes(Hunter et al., 2021). In another study, Bagdadi compared the Critical Acceleration Change (CAC) method with the longitudinal acceleration method in research focused on the hard braking indicator. The results showed that the CAC method performed approximately 1.6 times better than the longitudinal acceleration method in identifying hazardous situations leading to potential crashes (Bagdadi, 2013). Stipancic et al. investigated the impact of hard braking and sudden acceleration events on crash rates along road segments and at intersections. The findings revealed a direct relationship between the increased frequency of these conflicts and the number of crashes. However, the strength of this correlation was significantly higher at intersections, indicating a greater sensitivity of these locations to risky driving behaviors (Stipancic et al., 2018). Li et al. analyzed approximately 1.5 million hard braking events at signalized intersections, interchanges, and on/off ramps. The results indicated that high-risk areas can be identified using the hard braking indicator, and locations requiring geometric modifications or advanced warning signs can be effectively determined (Li et al., 2020b). Essa et al. utilized data derived from aerial video footage in their study and concluded that the highest number of traffic conflicts occurred during the initial seconds after the green light phase begins. This is when queues discharge at low speeds, and faster-approaching vehicles join the flow, leading to increased conflict occurrences (Essa and Sayed, 2019). Vajpayee et al. conducted a study using vehicle-based data collection methods to examine hard braking events at 435 signalized intersections, roundabouts, and stop-controlled intersections in the state of Indiana. The results indicated that signalized intersections and roundabouts recorded the highest number of hard braking (HB) events, while the normalized rate of this indicator was higher at all-way stop intersections. Additionally, the highest frequency of HB events occurred near the center of these intersections, whereas signalized intersections displayed a more uniform distribution. Furthermore, the speed of HB events was greater in the straight movements of signalized intersections, likely due to drivers' reactions to sudden changes in the yellow light phase (Vajpayee et al., 2024).

In general, it can be stated that limited studies have been conducted specifically on the hard braking indicator. Previous research has primarily focused on exploring the correlation between this indicator and crash frequency, aiming to confirm the significant direct relationship between hard braking events and crash occurrences. According to prior studies, this indicator has shown a significant correlation with crash occurrences at signalized four-way intersections (Hunter et al., 2021). Additionally, the definition of this indicator is based on the negative acceleration value. In previous studies, the critical value (negative acceleration) for this indicator has been considered to be 0.27 g, or it can be stated that the vehicle's speed should decrease by 18 miles per hour over a three-second period (Vajpayee et al., 2024). Additionally,researchers at GEOTAB have determined this critical value to be 0.49 g (Shen et al., 2024).Etemad, in the Euro FOT project, considered the negative acceleration for hard braking to be greater than 4 meters per second squared, or 0.41g (Etemad and Kessler, 2010).

What distinguishes this research is the examination of the impact of various traffic and geometric factors at signalized four-way intersections on the frequency and severity of hard braking events.It can be stated that the initial objective was to determine whether this indicator could serve as a replacement for traditional accident statistics studies. This issue having been confirmed,the present study now seeks to explore how each of the traffic and geometric factors may contribute to the increase in the severity and frequency of this indicator,and to what extent these factors influence accident occurrences.

3. Methodology

In traffic field studies, various methods are employed for data collection. The behavior of vehicles and their safety can be assessed using data obtained through video recordings from cameras. In the present study, which focuses on vehicle safety at signalized four-way intersections, aerial footage was captured using drones or unmanned aerial vehicles (UAVs) to provide an elevated perspective of the intersection. The primary objective of this research is to evaluate vehicle safety at signalized four-way intersections using the hard braking safety indicator, which serves as a critical metric for assessing potential hazardous conditions.

3.1. Hard Braking

The hard braking indicator refers to the frequency and severity of sudden braking events by drivers near intersections and serves as a measure for assessing hazardous conditions and geometric deficiencies in intersection design. This indicator is particularly useful at signalized intersections for analyzing the likelihood of rear-end collisions in queueing traffic or conflicts between left-turning and through-moving vehicles in two-phase intersection approaches.These events typically occur in response to sudden changes in traffic signals, unexpected stops by leading vehicles, or unforeseen obstacles. HB is defined based on the magnitude of negative acceleration or the rate of speed reduction per second. To identify a hard braking event, the vehicle's deceleration is calculated based on changes in speed over time.in this process, the speed difference at each point along the path, denoted as Δs_i, is defined as the difference between the speed sampled at point i and the speed at the previous point $(i-1)$ along the same path:

$$\Delta s_i = s_i - s_{i-1} \tag{1}$$

Additionally, the time difference at each point along the path, denoted as Δt_i, is equal to the difference between the sampled time at point i and the sampled time at point $(i-1)$ along the same path. In other words:

$$\Delta t_i = t_i - t_{i-1} \tag{2}$$

The acceleration at point i, denoted as a_i, can be expressed using the relationships given in equations (1) and (2) as follows:

$$a_i = \frac{\Delta s_i}{\Delta t_i} \tag{3}$$

This indicator helps identify intersection design issues, signal disruptions, and traffic flow inconsistencies in traffic safety models. It is especially important at signalized intersections due to the high likelihood of rear-end collisions. Data related to hard braking is collected through vehicle sensors, surveillance cameras, video analysis, or driving simulators. In this study, the method of aerial filming using a drone was employed. Analyzing these data allows for the identification of high-risk patterns and can serve as a basis for improving intersection design and optimizing traffic lights. Ultimately, this indicator plays a key role as an effective tool in traffic safety modeling, contributing significantly to the reduction of accidents and the improvement of traffic conditions.In previous studies, the critical value of negative acceleration for this indicator has been reported differently. Vajpayee reported the critical value as g 0.27, researchers from GEOTAB reported this value as g 0.49, and Etemad, in the Euro FOT project, reported the negative acceleration for hard braking as g 0.41. which approximately covers the range from 2.6 to 4.5 meters per square second. In this study, this indicator has been examined at five different values: -2.5, -3.0, -3.5, -4.0, and -4.5 meters per square second. In each time interval, the number of hard braking events at these specific values was recorded to determine whether traffic factors such as traffic volume, average speed, average entry speed, average exit speed, total distance traveled, the physical area of the intersection, and geometric factors such as intersection entry width, intersection exit width, the presence or absence of a median, island, speed bumps, and roundabouts influence the intensity and frequency of the hard braking indicator (HB). Furthermore, if they do have an impact, the extent of this influence is assessed.

3.2. Study locations and video data collection

The data and information used in this research were collected from seven signalized four-way intersections located in the city of Saqqez. The geographical location of Saqqez County and the intersections are shown in Figure (1).

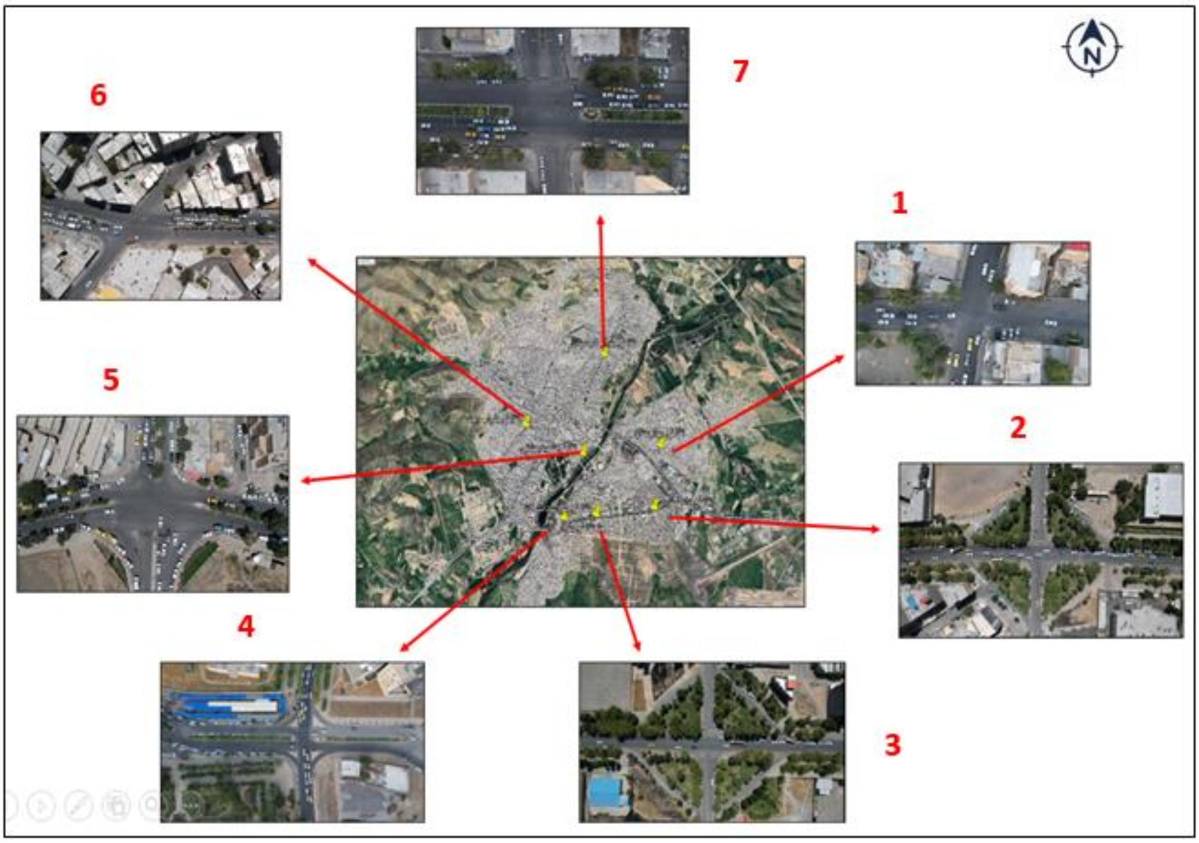

Figure 1. Intersection Locations in the Saqqez

The data collection process was carried out during pre-determined time intervals. These times were based on the historical traffic data available on Google Maps, during two daily time slots (12:00-13:00 PM and 18:00-19:00 PM), and were selected considering the field studies conducted by the research group and surveys from local residents in the area. The intersections studied in this research are located within the urban areas of Saqqez. All of these intersections have at least one main approach, and their pavement conditions are dry and normal. The required data for this research were collected through aerial filming using a drone. In order to obtain more accurate results, all data were recorded on non-holiday weekdays, excluding Thursdays, to avoid the impact of unusual traffic volume fluctuations on the results. Additionally, to ensure uniform environmental conditions, the filming was conducted in the summer season under stable weather conditions, without rain or strong winds. All of the intersections under study are two-phase controlled.

According to Figure 1, the intersections 1 to 7 are as follows: Salman Farsi Street - Amar Yasr, Daneshgah Boulevard - Sheikh Mazhar Street, Daneshgah Boulevard - Mohammad Ghazi Street, Daneshgah Boulevard - Daneshjou Boulevard, Shahid Beheshti Boulevard - Karfato Street, Vahdat Boulevard - Sangbaran Street, and Kurdistan Boulevard - Golestan Street Intersection.

The research was conducted using aerial filming with a Mavic Air 2S drone, as shown in Figure 2.

Figure 2. The drone used for video recording

3.3. Data Analysis and Image Processing

After the field film collection at the intersections, the footage required preparation and editing. After this, the recorded videos were analyzed using the Data From Sky (DFS) software. This advanced software is a valuable tool for traffic flow analysis and monitoring traffic conditions. DFS, utilizing advanced technologies such as image processing and artificial intelligence, enables the extraction of precise and real-time information from road and urban traffic. Key features of this software include traffic flow analysis, vehicle detection and tracking, road safety assessment, and optimal traffic management, all of which play a significant role in traffic studies and road safety. To evaluate the accuracy and reliability of the Data From Sky software, several validation methods have been employed. These methods include classified traffic volume counting, calculating the spatial average speed for different types of vehicles, and analyzing the microscale trajectories of experimental vehicles. Additionally, to assess the accuracy of the data extracted by DFS, the mean absolute error (MAE) was calculated, and the average speed of vehicles from both DFS data and field observations was compared. Furthermore, the accuracy of the vehicle paths extracted by DFS was evaluated using geographic location tracking on experimental vehicles. The results of this analysis demonstrate that data collected via drones or UAVs exhibit the least error and the highest accuracy, with a precision ranging from approximately 98% to 100% (Ali et al., 2024).

The DFS software identifies vehicle movements by analyzing the changes in each pixel of the images. After this step, the calibration process begins, and the image coordinates are converted to geographic coordinates (UTM) to determine the precise location of vehicles in the real-world space. Then, parameters such as speed, direction of movement, and traveled distance are calculated and transformed into analyzable traffic data. For calibration, at least four geographic coordinate points at the intersection are identified and recorded in the software. Saqqez County is located in UTM Zone 38, Northern Hemisphere, and the coordinates of these points must be determined according to this system. Subsequently, the processing and analysis of the videos will be carried out based on International System (SI) units, as shown in Figure (3).

After calibrating the software, the required data, including traffic variables, geometric variables (independent variables), and safety conflict indicators (dependent variables), are extracted. To examine the hard braking index, the traffic variables were obtained from the DFS software data. These variables include traffic volume, average speed, entry and exit speeds, vehicle acceleration, and total distance traveled. To calculate traffic volume, entry and exit gates (turnstiles) were determined for each branch of the intersection (as shown in Figure 4).

Figure 3. Before and After Software Calibration

Figure 4. Location of Entry and Exit Gates

By selecting the "Show Origin-Destination Statistics" option, an origin-destination matrix is generated, allowing for the classification of vehicle and pedestrian counts. To extract the total distance traveled, average speed, entry, and exit speeds, the "Export Traffic Analysis" option is selected, and the output Excel file is analyzed.

3.4. Modeling

One of the key tools in traffic safety research is statistical modeling, which enables researchers to evaluate the influence of various contributing factors on the target variable in this study, multiple linear regression was employed to analyze the influence of various contributing factors. This statistical model was selected because it enables both simultaneous and individual assessment of the effects of each independent variable on the safety indicator. Moreover, regression analysis allows for the numerical estimation and interpretation of the effect coefficients of each variable, providing a reliable prediction of safety conditions at intersections based on actual input values. Ultimately, this model serves as an analytical tool that provides a foundation for assessing the safety status of intersections and supports engineering and managerial decision-making in the field of urban traffic management. A multiple linear regression model is represented by Equation (4).

$$Y = \beta_0 X_0 + \beta_1 X_1 + \cdots + \beta_N X_N + \varepsilon \qquad (4)$$

In Equation (4), Y is the dependent (or explained) variable, while X_0, X_1, ..., X_n are the independent variables. The coefficients β_0, β_1, β_2, ..., β_n represent the regression weights associated with each independent variable. The term ε denotes the error term, which is assumed to follow a normal distribution and accounts for the variation in Y that cannot be explained by the independent variables (Wooldridge, 2016).

In this study, the count data are not well-suited for a linear regression model, as the assumptions of the model such as normality of residuals, homoscedasticity, and linearity of relationships may be violated. To address this issue, a square root transformation is applied. This transformation helps reduce heteroscedasticity, decrease the skewness of the distribution, and improve the linearity between variables. As a result, it enhances the accuracy and reliability of the regression model. In this section, the coefficients of the linear regression model will be analyzed and interpreted after applying the square root transformation to the dependent variable. Following this transformation, the regression model takes the form shown in Equation (5).

$$\sqrt{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_N X_N + \varepsilon \quad (5)$$

In this new model, the coefficient β_i represents the change in $\sqrt{Y}$ for a one-unit change in X_i. To interpret the coefficients β_i in the original scale of Y, it is necessary to compute the changes in Y after applying the square root transformation. Assuming that X_i changes by one unit, this change will cause a change in $\sqrt{Y}$ by β_i. Therefore, Equation (6) is obtained.

$$\Delta\sqrt{Y} = \beta_i \quad (6)$$

To calculate the changes in Y after reverting to the original scale (since $Y=(\sqrt{Y})^2$), Equation (7) can be used.

$$Y_{new} = \left(\sqrt{Y} + \beta\right)^2 = Y + 2\beta\sqrt{Y} + \beta^2 \quad (7)$$

And if $\Delta Y = Y_{new} - Y$, then Equation (8) will be obtained.

$$\Delta Y = 2\beta\sqrt{Y} + \beta^2 \quad (8)$$

Based on the derived expression, the obtained coefficients can be interpreted directly by considering the average of the dependent variable ($\sqrt{Y}$) for each value of the studied indices, allowing for a direct interpretation of the impact of each factor (Neter et al., 1996).

4. Results and Discussion

In this section, the results obtained from the analyses are presented, and a discussion regarding these results is provided.

One of the important steps in modeling is the clear and transparent presentation of variables. In this section, the different types of variables used in the model are provided. Table1 presents the dependent variables of the model, with the Hard Braking (HB) index examined at five different values, as mentioned earlier. Additionally, Table2 shows the independent variables of the model.

Table 1. dependent variables of the model

Variable unit	Name Variable	Variable abbreviation
Frequency	Sqrt Frequency Hard Braking	Sqrt FHB< (-2.5$\frac{m}{s^2}$)
Frequency	Sqrt Frequency Hard Braking	Sqrt FHB < (-3.0$\frac{m}{s^2}$)
Frequency	Sqrt Frequency Hard Braking	Sqrt FHB < (-3.5$\frac{m}{s^2}$)
Frequency	Sqrt Frequency Hard Braking	Sqrt FHB < (-4.0$\frac{m}{s^2}$)
Frequency	Sqrt Frequency Hard Braking	Sqrt FHB < (-4.5$\frac{m}{s^2}$)

Table 2. Independent variables of the model

Variable unit	Name Variable	Variable abbreviation
Veh/time	Traffic Volume	TrV
Km/h	Average Speed	AS
Km/h	Average Speed Entry	ASEn

Variable unit	Name Variable	Variable abbreviation
Km/h	Average Speed Exit	ASEx
M	Total Distance Traveled	TDT
m^2	Physical Area	PhA
M	Average Width Entry	AWEn
M	Average Width Exit	AWEx
-	U-Turn	U-T
-	BUMP	BUMP
-	Island	Is
-	MEDIAN	MEDIAN

For modeling the linear regression of the Hard Braking (HB) index, which is evaluated based on the negative acceleration of each vehicle and is related to the driving behavior independent of other vehicles, the normality of the dependent variable was first examined. The results of the tests are shown in Table 3. Based on the Kolmogorov-Smirnov and Shapiro-Wilk tests, it can be determined whether the dependent variable is normal or not. The null hypothesis (H_0) for these tests assumes normality, and if the significance is greater than 0.05, then the null hypothesis is not rejected, indicating that the variable is normal. Based on Table 3, for the dependent variable of the model (HB4.5), the results of the normality test from SPSS indicate that the variable is normal, and the null hypothesis (H_0) is not rejected.

Table 3. The result of the normality test for the dependent variable

Kolmogorov-Smirnov-test	Shapiro-Wilk
Sig.	Sig.
0.200	0.404

Then, the significance of the independent variables and the model's correlation for the five different levels of the Hard Braking (HB) index are analyzed. After performing correlation tests and examining the significance of the variables individually, some of the independent variables were removed from the model. The removed variables are as follows the average speed (the average speed of all vehicles in the physical area of the intersection), the presence of triangular islands, the average entry width (the average width of the entry approaches), the average entry speed (the average speed of vehicles entering the intersection), the average exit width (the average width of the exit approaches), the presence of roundabouts, the area of the physical zone, and the total distance traveled (the total distance traveled by vehicles in the physical area of the intersection) are the variables that were removed.

A summary of the statistical results for the dependent variable sqrt (HB4.5) is presented in Table 4. As previously mentioned, in order to apply multiple linear regression, the square root transformation of the count data for the HB index can be used. Afterwards, the transformed variables can be converted back to their original values. Based on the results presented in Tables 4 to 8, it can be inferred that, among the independent variables listed in Table 2, traffic volume (TrV), average exit speed (ASEx), the presence of speed bumps (BUMP), and the presence or absence of a median (MEDIAN) exhibit statistically significant associations with the hard braking (HB) index within the context of this study. Based on the statistical tables provided, it can be concluded that an increase in traffic volume at signalized four-leg intersections is associated with a rise in the number of hard braking (HB) events. This suggests that higher traffic density may increase the likelihood of sudden deceleration maneuvers due to more frequent vehicle interactions and reduced maneuvering space. Furthermore, the analysis indicates that higher average exit speeds from intersections also correlate with an increased number of hard braking incidents. This may reflect the influence of higher driving speeds on the reduced reaction time and safety margins, thereby intensifying the probability of abrupt braking in conflict situations. Moreover, based on these findings, it can be inferred that the presence of speed bumps on the entry approaches of intersections can lead to an increase in the frequency of hard braking by drivers. Additionally, the existence of a median also appears to have a positive effect on the number of hard braking events, contributing to a rise in this safety-related indicator. This increase can be attributed to the reduced lane width and decreased flexibility for drivers in making decisions when approaching the intersection. In such situations, drivers have less maneuvering space to avoid collisions or to decelerate gradually, which leads to a rise in sudden braking events.

As shown in Table 4, the Variance Inflation Factor (VIF) values are all below the critical threshold of 10, indicating that there is no severe multicollinearity among the independent variables in the model. According to Table 5, the R-Squared value is 0.776, meaning that approximately 78% of the variation in the dependent variable is explained by the included predictors. The small difference between R-Squared and Adjusted R-Squared suggests that the model is not overfitted and that the sample size is appropriate relative to the number of explanatory variables. Additionally, the results of the White test indicate that for all models, the significance values exceed 0.05. Therefore, the null hypothesis of homoscedasticity is not rejected, confirming that the assumption of constant variance of the residuals holds true across the models.

Table 4. Estimation results of the model variable coefficients SqrtFHB(-4.5)

VIF	Significance	Coefficients (β)	Variables
	0.001>	1.45	Constant
7.38	0.001>	0.022	TrV
1.59	0.001>	0.12	ASEx
2.48	0.001>	1.60	BUMP
9.12	0.001>	1.16	MEDIAN
R-Square=0.786	Adj R-Square=0.783	Sig. of White Test =0.427	

Table 5. Estimation results of the model variable coefficients SqrtFHB(-4.0)

VIF	Significance	Coefficients (β)	Variables
	0.001>	1.69	Constant
7.38	0.001>	0.024	TrV
1.59	0.001>	0.13	ASEx
2.48	0.001>	1.66	BUMP
9.12	0.001>	1.15	MEDIAN
R-Square=0.776	Adj R-Square=0.772	Sig. of White Test =0.397	

Table 6. Estimation results of the model variable coefficients SqrtFHB(-3.5)

VIF	Significance	Coefficients (β)	variables
	0.001>	2.19	constant
7.38	0.001>	0.025	TrV
1.59	0.001>	0.12	ASEx
2.48	0.001>	1.84	BUMP
9.12	0.001>	1.40	MEDIAN
R-Square=0.783	Adj R-Square=0.779	Sig. of White Test =0.124	

Table 7. Estimation results of the model variable coefficients SqrtFHB(-3.0)

VIF	Significance	Coefficients (β)	variables
	0.001>	2.67	constant

VIF	Significance	Coefficients (β)	variables
7.38	0.001>	0.029	TrV
1.59	0.001>	0.12	ASEx
2.48	0.001>	1.89	BUMP
9.12	0.001>	1.50	MEDIAN
R-Square=0.774	Adj R-Square=0.770	Sig. of White Test =0.259	

Table 8. Estimation results of the model variable coefficients SqrtFHB(-2.5)

VIF	Significance	Coefficients (β)	variables
	0.001>	3.30	constant
7.38	0.001>	0.035	TrV
1.59	0.001>	0.13	ASEx
2.48	0.001>	1.89	BUMP
9.12	0.001>	1.59	MEDIAN
R-Square=0.754	Adj R-Square=0.750	Sig. of White Test 0.184	

Based on Equation ($\Delta Y = 2\beta\sqrt{Y} + \beta^2$) and the mean values obtained for the five different levels in Table 9, the exact coefficients for the independent variables can be determined. Using these coefficients, the precise effect of each independent variable on the dependent variable can be calculated. This means that the change in the number of critical events of the Hard Braking (HB) index can be determined based on the coefficients of the independent variables. Now, it can be stated that, according to Table 10, the actual or adjusted coefficients of the independent variables have been obtained.

The factors and variables affecting the severe braking index, along with the actual coefficients, are presented in this table. Five models were constructed for this index at different negative acceleration intervals, and their summaries are provided in the corresponding table. The results of the models indicate that an increase in traffic flow rate can lead to an increase in the number of severe braking events at each negative acceleration interval. Specifically, an increase in traffic volume has a greater impact on the number of critical conflicts with an intensity of less than -2.5 m/s², with this effect estimated to be about 2.33 times greater than the conflicts with an intensity of less than -4 m/s².

Table 9. average of sqrt hard braking for HB range

average of sqrt hard braking($\sqrt{Y_{HB}}$)	($\frac{m}{s^2}$)HB Range
6.86	HB(-4.5)
7.43	HB(-4.0)
8.10	HB(-3.5)
8.95	HB(-3.0)
10.05	HB(-2.5)

Table 10 . Actual coefficients of independent variables

	FHB(-2.5)	FHB(-3.0)	FHB(-3.5)	FHB(-4.0)	FHB(-4.5)
TrV	0.70	0.52	0.41	0.36	0.30
ASEx	2.63	2.16	1.96	1.95	1.66
BUMP	41.56	37.40	33.19	27.42	24.51
MEDIAN	34.49	29.10	26.64	18.41	15.92
R-Square	0.754	0.774	0.783	0.776	0.786

Additionally, an increase in the average exit speed from each intersection approach can lead to an increase in the number of critical severe braking events. According to the actual coefficients in Table 10, it can be stated that an increase of 1 km/h in the exit speed from each intersection approach can increase severe braking events with decelerations of -4.5 m/s², -4.0 m/s², -3.5 m/s², -3.0 m/s², and -2.5 m/s² by 3.4%, 3.3%, 2.9%, 2.6%, and 2.5%, respectively, in each traffic light cycle.

Additionally, based on the obtained coefficients, it can be stated that the presence of speed bumps leads to an increase in severe braking events. Specifically, the presence of a speed bump in each intersection approach can increase severe braking events with decelerations of -4.5 m/s², -4.0 m/s², -3.5 m/s², -3.0 m/s², and -2.5 m/s² by 48%, 47%, 47%, 44%, and 38%, respectively. This increase is natural, considering the reduction in speed required by the driver when encountering a speed bump, even when the traffic light is green.

5. Conclusion

The main objective of this study, as mentioned at the beginning, is to examine the impact of geometric and traffic factors on safety at four-legged urban intersections, which is assessed through the analysis of traffic safety indicators such as Hard Braking (HB). To achieve the research objectives, the necessary data were collected through aerial filming at seven intersections. The impact of geometric and traffic variables on the Hard Braking index was investigated at various critical levels. The data were analyzed using SPSS software and modeled using five multiple linear regression models. These analyses demonstrate the relationship between independent variables and traffic safety. In this section, the findings of the study will be presented, and it should be noted that the results are both quantitative and qualitative.

The analysis of the results related to the traffic volume (TrV) variable showed that an increase of one unit in the number of passenger vehicles can increase the frequency of HB (Hard Braking) events. Based on the coefficients, it can be concluded that the effect of increasing this variable on the Hard Braking index for different acceleration values is as follows:

$$HB_{-4.5} < HB_{-4.0} < HB_{-3.5} < HB_{-3.0} < HB_{-2.5}$$

This means that the effect of increasing one unit of passenger vehicles decreases as the acceleration becomes smaller. Increasing one unit of passenger vehicles raises the number of critical events for the HB(-2.5) index by 2.34 times more than for the HB(-4.5) index. Additionally, an increase of one unit in the traffic volume (i.e., one passenger vehicle) increases the number of critical events or severe braking events for the HB index with accelerations of less than -4.5, -4.0, -3.5, -3.0, and -2.5 m/s² by 0.30, 0.36, 0.41, 0.52, and 0.70 (6.0%) respectively.

The impact of the average exit speed variable (ASEx) on the HB index is significant, and the effect of this variable on the safety index is positive. That is, as the exit speed of vehicles increases, the number of severe braking events increases. Moreover, an increase of 1 km/h in this variable raises the number of critical events with deceleration rates of −4.5, −4.0, −3.5, −3.0, and −2.5 m/s² by approximately 1.66, 1.95, 1.96, 2.16, and 2.63 occurrences, respectively (approximately a 3% increase).

The presence or absence of speed bumps has a statistically significant effect on the HB traffic safety indicator. The presence of speed bumps increases this indicator, and based on the variable coefficients and the total number of critical events, it can be inferred that speed bumps increase the number of critical hard braking events with deceleration rates of less than −4.5, −4.0, −3.5, −3.0, and −2.5 m/s² by approximately 48%, 47%, 47%, 44%, and 38%, respectively.

5.1. Limitations

Despite the valuable findings of this study, several limitations must be considered when interpreting the results. First, the spatial scope of the analysis was restricted to only seven four-leg signalized intersections within a single urban area, which may limit the generalizability of the findings to other locations with differing geometric configurations and traffic characteristics. Second, the data were extracted through drone-based video analysis, which, due to temporal constraints during image capture, covered only a limited portion of daily traffic conditions. To overcome this limitation, future studies are encouraged to incorporate high-resolution, time-continuous data obtained from in-vehicle sensors, such as accelerometers or connected vehicle data logging systems, to enhance the precision and reliability of Hard Braking (HB) analysis. Furthermore, while HB is recognized as a practical and operational surrogate safety measure, it may not fully capture the interactive and dynamic aspects of driver behavior at intersections. Compared to more interaction-sensitive indicators like Time-to-Collision (TTC) and Post-Encroachment Time (PET), HB alone may provide a less comprehensive representation of potential conflict scenarios.

5.2. Future Research Directions

Building upon the findings and limitations of the present study, several promising avenues for future investigation are identified. These research directions aim to deepen the understanding of hard braking behaviors and enhance safety evaluation methodologies at signalized urban intersections. The following topics highlight critical gaps and emerging technologies that warrant further exploration:

1. Assessment of Advanced Driver Assistance Systems (ADAS) on Mitigating Hard Braking Events at Signalized Urban Intersections.

This research avenue involves quantifying the effectiveness of ADAS technologies in reducing the frequency and severity of hard braking incidents, thereby enhancing intersection safety and traffic flow efficiency.

2. Development of Machine Learning Models for Predictive Analytics of Hard Braking Events Using High-Resolution In-Vehicle Sensor Data.

Leveraging continuous, high-fidelity sensor data from connected vehicles, this line of research focuses on employing state-of-the-art machine learning algorithms to identify critical precursors and accurately forecast abrupt braking behaviors in complex traffic environments.

3. Comparative Evaluation of Surrogate Safety Measures: Hard Braking (HB), Time-to-Collision (TTC), and Post-Encroachment Time (PET) for a Multidimensional Safety Assessment Framework at Urban Intersections.

A systematic comparison of these key safety indicators aims to formulate an integrated risk assessment model that captures both individual and interactive driver behaviors influencing collision potential.

4. Investigation of Geometric Design Factors Influencing Hard Braking Frequency Using Field Data and Advanced Statistical Modeling.

This research seeks to elucidate the impacts of intersection geometric attributes — such as stop line length, sight distance, and lane configuration —on driver deceleration patterns, employing rigorous statistical methods and real-world traffic data.

5. Behavioral Analysis of Hard Braking Incidents Under Varied Traffic Flow Conditions: Contrasting High-Volume Versus Low-Volume Urban Intersections

Examining how traffic density and temporal demand fluctuations affect driver braking responses, this study intends to delineate context-specific risk profiles to inform adaptive traffic management strategies.

6. Evaluation of the Efficacy of Driver Safety Training Programs on Reducing Hard Braking Incidents: A Field-Based Empirical Study Across Diverse Urban Settings.

This research evaluates the impact of targeted driver education interventions on modifying aggressive driving behaviors, measured through changes in surrogate safety metrics, to support evidence-based policy and training program development.

6. Ethical Note

A portion of the manuscript preparation process was assisted by Artificial Intelligence (AI) tools to enhance clarity, coherence, and academic style. All analyses, interpretations, and final conclusions remain the sole responsibility of the authors.

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