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Comparison of common methods for determining hazardous locations for improving road safety

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ABSTRACT

Identifying hazardous locations is crucial for maximising benefits from road safety investments. Using an appropriate method for identifying hazardous road locations (HRL) is essential due to limited research on existing approaches. This study evaluated the effectiveness of the four most commonly used approaches to prioritise HRLs such as crash frequency (CF), crash rate (CR) Empirical-Bayes (EB) adjustment and potential for safety improvement (PSI). This study used six years (2010–2015) of severe-crash data collected from 80 highway segments in Toowoomba, Australia. Crash prediction models were created to anticipate crash expectations. The negative binomial technique was found to be suitable for developing the models. These HRL identification techniques were assessed using rigorous quantitative criteria, such as the site consistency test, the total-rank differences test, the method consistency test and the total-score test. Our data demonstrate that the EB approach significantly outperformed the other ranking strategies. In contrast, the CR method consistently underperformed because of its inherent bias towards low-traffic sites. Notably, this technique assumes a linear relationship between CRs and traffic volume, despite earlier research proving the normal nonlinearity of this connection. As a result of this study, road engineers can develop models to predict crash trends and use the EB approach to prioritise treatment sites and identify the most hazardous locations for safety improvements. In conclusion, building on our current findings and prior research, we strongly recommend that the EB adjustment approach be adopted as the standard for determining HRLs unless alternative methods emerge to replace it.

Introduction

Identifying hazardous road locations (HRLs) is an essential to improve road safety. Resources can be wasted on locations that have been identified incorrectly as hazardous, and whereas truly hazardous locations remain untreated if not identified properly. In general, there is some crash risk on all roadways. However, certain road sites (e.g. intersections and segments) are considered more hazardous than others. Not surprisingly, various physical characteristics, meteorological conditions, operational components and traffic volumes result in heterogeneity in crash risk levels. Therefore, identifying HRLs is critical for enhancing road safety, especially when road safety authorities operate on a limited budget.

The identification of HRLs is usually considered the initial phase of a crash-reduction process. HRLs are sometimes referred to 'black spots', 'hotspots', or 'crash-prone locations'. According to Al-Marafi et al. (2020) and Hauer et al. (2002), identifying HRLs signifies a list of locations selected for additional research and technical investigations that have helped characterise collision patterns, emotional factors, and potential countermeasures. To make investment decisions with limited resources, experts use cost-effective identification methods to choose road safety projects. This study identified HRLs using two approaches based on: crash data and models. The first method is based on historical accident data, in which HRLs are defined as locations with more than a present crash frequency (CF) (e.g. crash per km or crash per year) or crash rate (CR) (e.g. crash per vehicle km). The second technique is model-based assessment, in which statistical models are applied to estimate the severity at each site, referred to as 'black spots' (AASHTO, 2010).

Desai et al. (2021) investigated the correlation between hard braking events and road crashes using data from 23 sites along Indiana interstate roadways over two months. The study revealed that around one crash happened for every 147 hard braking events per mile. The use of hard braking data has the potential to assist agencies in prioritising safety

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investments. This approach allows for proactive decision-making without the necessity of waiting for crash history to evolve over time on a particular roadway under evaluation. However, this approach requires vehicles to have connected devices. These devices can monitor and record live operational data, including location, speed, and hard braking events (Desai et al., 2021; Feng et al., 2024).

Elvik (2008) identified and ranked hazardous locations using CF, CR, and a combination of CF and empirical-Bayes (EB) methods. According to the results, the EB method performed the best, whereas the CR method performed the worst. Cheng and Washington (2008) and Montella (2010) validated this finding. According to Al-Marafi et al. (2019) and Elvik (2007), the optimal technique for determining HRLs is the expected crash frequency and not observed crashes. The most accurate technique to calculate the expected crash frequency is to combine the number of recorded crashes with the model estimate for a particular location. Using the EB approach is an effective way to do this. It is noteworthy that the EB method eliminates regression-to-the-mean (RTM) bias by generating a weighted average of actual and anticipated crashes (Al-Marafi, 2019; Abdel-Aty et al., 2014; Elvik et al., 2017; B. Persaud and Lyon, 2007; Tegge et al., 2010). According to Persaud and Lyon (2007) the RTM phenomenon is caused by the tendency of locations (e.g. roadway segments) with a high collision frequency in one year to regress to a lower CF in the next year. Thus, for a site that experienced many crashes in a particular year, the random nature of the crashes suggests that CF is likely to decrease the next year, even without treatment or changes in traffic conditions. This regression is expected to bring the CF closer to the long-term mean value. According to Elvik et al. (2017), the EB method helps researchers to account for RTM bias, long-term trends and exogenous fluctuations in traffic flow.

The Poisson distribution and negative binomial (NB) models are considered more suitable for constructing crash prediction models (CPMs) because of the inherent characteristics of crash occurrences, which are inevitable, discrete and often exhibit random behaviour (Abdel-Aty and Radwan, 2000; Ackaah and Salifu, 2011; Hadi et al., 1995; Pew et al., 2020). According to Abdel-Aty and Radwan (2000), several limitations and restrictions are associated with the use of the Poisson distribution technique. In crash data, the variation in crash numbers is generally more than the mean; in such cases, the data are excessively dispersed. To overcome the restriction of over-dispersion in the Poisson distribution technique, a few studies (Al-Marafi et al., 2021; Al-Marafi, 2019; Chin and Quddus, 2003; Gargoum and El-Basyouny, 2016; Lord and Mannering, 2010) recommend using other methods. As a result, they propose using NB model as an alternative because it does not need the assumption of equal mean and variance.

Ensuring the success of safety improvement programs in reducing roadway crashes depends on the availability of techniques that offer valid estimations of highway safety level. These estimations should be relevant to current roadway conditions and future scenarios, such as treatment implementation. The primary objective of this study was to assess the available methods used for identifying and ranking HRLs for safety improvement. The 2010–2015 crash data from Toowoomba, Australia, were used to compare a few common methods. The CPMs for roadway segments were initially developed and evaluated for all serious-crashes. To select the most suitable method, the performances of different ranking methods, such as CF, CR, EB adjustment and potential for safety improvement (PSI) methods, were compared. To evaluate performance, the following robust quantitative testing criteria were used: (i) site consistency test (SCT), (ii) total rank differences test (TRDT), (iii) method consistency test (MCT) and (iv) total score test (TST).

The remainder of this paper is structured as follows: initially, it describes the data that was utilised in the analysis. Then, it provides previous research on HRL identification methods and the development of CPMs. The following section examines the process of creating and evaluating models and presents the results of the applied HRL identification techniques. Finally, the concluding section summarises the study's findings with recommendations.

Crash data preparation

Crash data for the Toowoomba city roadway segments were obtained from the Department of Transport and Main Roads (DTMR), Queensland. The details of speed limit, type of traffic control, crash location, crash time and crash severity were acquired for each crash data of the designated road segments. The traffic volume data were obtained from both the Toowoomba Regional Council (TRC) and the DTMR. Data on the geometric characteristics of roadway segments were obtained from site visits and historical design records from the TRC. The historical records of treatments applied to roadway segments during the study period, considering both geometric and traffic characteristics, were reviewed using historical data from TRC and DTMR. This step was crucial to identify and exclude any segments that changed during the study period. By doing so, the study aimed to prevent bias in the analysis results of the model. Finally, from a sample size of 80 roadway segments, and 301 records of serious crashes were obtained.

The following principles were applied to segment the road. According to the first criterion, a roadway segment was defined as any portion of the road situated between two major intersections. In particular, the defined intersection boundary was excluded, and the borders of a road segment were determined by the presence of two nearby intersections, as shown in Fig. 1. The intersection boundary was defined as a 20-meter area measured upstream from the stop line (Al-Marafi et al., 2021). Any crashes with geo-coordinates falling within this boundary were considered intersection-related and excluded from the analysis. The second criterion stipulated that a road segment should be homogeneous, meaning that any differences from the modelling risk would be minimised. Consistent and uniform values were maintained for all explanatory variables, including traffic volume, number of lanes, shoulder width, lane width and speed limit. Considering all things, creating a new roadway segment was possible either by the existence of two nearby intersections or based on previously specified roadway attributes.

Roadway segments were chosen based on their geographical location within the study area to avoid bias towards high or low CF locations. The study period covered six years (from 2010 to 2015). Independent variables related to crashes in roadway segments were represented by geometric parameters and traffic volume. Table 1 summarises the independent variables included in the safety models and shows how they were defined within the dataset.

Each segment has two directions of traffic flow, and AADT value includes traffic on both directions. Depending on the direction of travel, traffic on each segment must use either an upward or downward gradient. Therefore, this study used the gradient's absolute value, resulting in a positive value for all segments.

Crash prediction models

CPMs were developed with the goal of estimating the expected number of crashes. These estimates are essential for applying EB and PSI ranking techniques, contributing to assessing and prioritising roadways' safety measures.

There have been many research papers (Sacchi et al., 2012; Sun et al., 2012; Xie et al., 2011) on the calibration and validation of the crash prediction models used in the HSM. They investigated the transferability of HSM crash prediction approach and discovered that they were consistent with the homogeneous segmentation of the selected study roads. Xie et al. (2011) indicated that the HSM overestimated crash numbers. Abdel-Aty et al. (2014) summarised developing a statewide calibration factor, calibration factors specific to different types of crashes, calibration based on the frequency of animal-related crashes by county, and calibration based on the frequency of animal-related crashes by section to address variations in estimation. Due to the complexity of the HCM approach, many of these studies employed

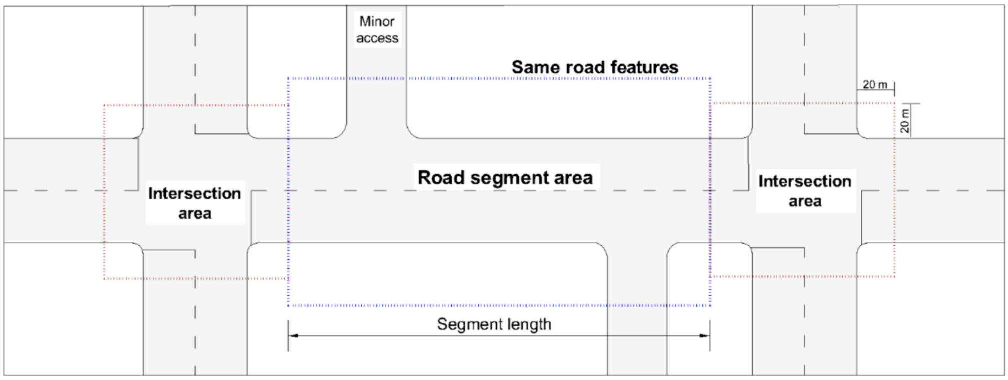

Fig.1. Roadway segment as defined in the study.

Table 1
Summary statistics of the segment's explanatory variables.

Variables	Min	Max	Mean	Std. deviation	Symbol	Variable type
Segment length, (km)	0.190	1.500	0.530	0.212	*Ls*	Continuous
Traffic volume, AADT	2500	21,800	10,960	4874.3	*Q*	Continuous
Lane width (m)	2.9	4.8	3.92	0.851	*Wl*	Continuous
Shoulder width (m)[a]	0	5.0	1.10	1.681	*Ws*	Continuous
Number of lanes per direction	1.0	2.0	1.37	0.483	*N*	Count
Access points	0	11	2.84	1.768	*A*	Count
Presence of median	0	1	0.18	0.392	*M*	Categorical
Presence of road marking						
Centre line	0	1	0.90	0.276	*Cl*	Categorical
Edge line	0	1	0.47	0.499	*El*	Categorical
Grade (%)	0.45	8.85	3.63	1.821	*Gr*	Continuous
Speed Limit (kph)	40	70	58.9	3.842	V_s	Continuous

[a] combined width; AADT=annual average daily traffic (vpd).

empirical Bayes (EB) method to enhance accuracy.

Montella (2003) study on the Potential for Safety Improvement (PSI) index found it eliminates the need for preliminary data in safety reviews of existing roads. The index complements safety reviews in many highway agencies worldwide, ranking reviewed segments or safety issues. Different PSI indexes can be computed, identifying safety concerns where cost-effective improvements may be made. The overall index measures potential safety improvement in all segments. A team with sound safety engineering knowledge is necessary for improved reliability.

Selecting explanatory variables

When analysing data from roadway segments, the explanatory variables may be interrelated. Pearson's correlation analysis measures the connection between two explanatory variables and assists in determining the degree of a correlation between any two sets of variables. According to Navidi (2008), the model estimate could be erroneous if the predictor variables are significantly correlated, typically in the range between ± 0.50 and 1.00. The standard error of the regression model rises when the two explanatory parameters have significant correlations. As a result, the correlation values for each predictor variable in this study were determined. Variables with correlation values between −0.49 and + 0.49 (moderate correlation) were incorporated into the modelling. The parameters were judged statistically significant at the 0.05 significance level with a confidence level of 95 %. Table 2 presents the correlation coefficient matrix among the independent variables employed in selecting the appropriate model. The correlation matrix reveals a strong correlation between the following variables: traffic volume with lane width; lane width with number of lanes per direction; and shoulder width with the presence of edge line road marking. As a result, these variables were not included simultaneously in the modeling process to mitigate issues related to multicollinearity.

Selecting suitable modelling approaches

Road crash distributions were initially assumed to have an NB distribution. Later, generalised linear models were used to develop the models using identified explanatory variables. Regression analyses were performed using SPSS (version 22) under the assumption of NB models with a log link function. The general form of the predicted model for the i^{th} roadway segment can be written as follows:

$$N_{pre.i} = Ls_i^{\alpha 1} Q_i^{\alpha 2} . e^{\beta_0 + \sum_{j=1}^{n} \beta_j X_{ij}} \tag{1}$$

where: $N_{pre.i}$ – predicted crash frequency; Ls_i – roadway segment length in metres; Q_i – annual average daily traffic (AADT) in vehicle/day; X_{ij} – explanatory variable *j*; and α_1, α_2, β_0, and β_j – model parameters.

The over-dispersion assumption helps check the suitability of the models. This assumption was tested by estimating and examining two values: Pearson's chi-square (x^2) divided by the degree of freedom (*dof*) and the deviance divided by the *dof*. The assumption of the NB model may be used when the sum of these two numbers falls between the range of 0.80 and 1.20 (Al-Marafi et al., 2021; Ackaah and Salifu, 2011). Otherwise, other models, such as the Poisson distribution, need to be considered in modelling (Al-Marafi et al., 2020; Abdul Manan et al., 2013; Bauer and Harwood, 2000).

Model evaluation

To evaluate the models' validity, some goodness-of-fit (GOF) measures were required, because no single measure could achieve a complete desired outcome. The GOF measures for the selected models were examined by using many statistical approaches, including the Akaike information criterion (AIC), Freeman-Tukey R-Squared coefficient (R^2_{FT}), mean squared prediction error (MSPE), Bayesian information criterion (BIC), and mean squared error (MSE). AIC and BIC are used to assess the fit of the estimated distributions for the data and to identify the most suitable distributions. Abdul Manan et al. (2013) and Cafiso

Table 2
Correlation matrix for independent variables.

Variables	*Ls*	*Q*	*Wl*	*Ws*	*N*	*A*	*M*	*Cl*	*El*	*Gr*	V_s
Ls	1										
Q	-0.302	1									
Wl	0.124	-0.506	1								
Ws	0.019	0.201	-0.353	1							
N	-0.418	0.414	-0.611	0.264	1						
A	0.425	-0.148	0.109	-0.135	-0.117	1					
M	-0.246	0.149	-0.092	0.26	0.340	-0.229	1				
Cl	0.018	0.407	-0.308	-0.021	0.233	-0.038	-0.405	1			
El	0.027	0.244	-0.459	0.708	0.195	-0.106	0.282	0.012	1		
Gr	0.109	-0.056	0.082	-0.231	-0.146	0.014	-0.124	0.155	-0.173	1	
V_s	0.182	0.461	-0.007	-0.101	0.210	0.181	-0.194	0.279	-0.114	0.083	1

et al. (2010) found that models with reduced AIC and BIC values were more favourable than models with higher values. In other words, lower AIC and BIC values signify a smaller discrepancy and a better fit of the developed model to the data. In this study, the MSPE, MSE, and R^2_{FT} values were also used to evaluate the models' effectiveness in predicting road crashes over subsequent years. MSPE is used as a tool to calculate the variability of the discrepancy between predicted and observed crash numbers. Additionally, it is used to compute the errors associated with a validation dataset. The MSE is commonly used to quantify errors associated with an estimation dataset. The R^2_{FT} is used to calculate the average of the prediction variability including both the estimation and validation datasets. A higher value of R^2_{FT} indicates that the model exhibits a stronger fit for the data used.

Model results and interpretation

After several trials with different variables, a crash model was identified and estimated using NB distribution with a log correlation function. The computed regression parameters for the chosen model are shown in Equation (2).

$$N_{pre.i} = Ls_i^{.338} \times Q_i^{.529} \times e^{(-6.271-.410M+.031Gr)} \tag{2}$$

where: $N_{pre.i}$ – predicted CF along the roadway segment for three years (2010–2012), Ls – length (m) of the roadway segment, Q_i – AADT in vehicles/day, M – the presence of a median island (1 – present, 0 – absent), and Gr – the percentage of the absolute gradient, i.e., positive value for both gradient. The over-dispersion parameter (k) of the NB distribution was also derived during the regression calibration process and was determined to be 0.520.

The variance inflation factor (VIF) was utilised to evaluate the collinearity of the variables in the final developed model. This statistical test was used to calculate the multicollinearity level for each variable in a developed model. A variable with a VIF greater than 10 has to be removed from the model as it indicates the presence of high multicollinearity (Dadashova et al., 2016). The VIF values for the variables included in the model (Equation (2) were as follows: Ls = 1.144, Qi = 1.061, M=1.088, and Gr = 1.025. According to these values, the variables in the developed model do not have any collinearity problems.

The calculated GOF measures demonstrate the predicted model's fit to the dataset. The deviation and Pearson Chi-squared values were divided by the *dof* to estimate the GOF value, as shown in Table 3. Significantly, the GOF values were within the accepted range of 0.80–1.20, meaning that the NB distribution assumption was adequate to represent the data. Table 2 also shows the AIC and BIC values as effectiveness indicators for the predicted model.

Table 4 shows the validation results obtained by three performance measures, including MSPE, MSE, and R^2_{FT}. When comparing the MSPE and MSE values from the validation and estimation datasets, it is clear that the value of MSPE from the validation dataset was somewhat higher than the MSE value from the estimation dataset. This indicates that the chosen model is slightly over-fitted. Furthermore, the R^2_{FT} value for the validation dataset is lower than for the estimation dataset, however, the overall difference is not significant. The findings is reasonable because these values are not determined from the same data points. However, the results designate that the model works effectively over additional years of data. The previous discussions have led to the conclusion that the model is statistically sound and could be accepted for further investigation.

Table 3
Goodness-of-fit (GOF) tests for the selected model.

Criterion	Label	Value	*dof*	Value/*dof*
Deviance	–	84.050	79	1.066
Pearson's chi-Squared	x^2	69.861		0.862
Akaike's info. criterion	AIC	284.091		.
Bayesian info. criterion	BIC	298.175		.

Table 4
Validation results for the selected model.

Performance measure	Estimation data (2010 – 2012)	Validation data (2013 – 2015)
MSPE	–	2.331
MSE	1.763	–
R^2_{FT} %	25.0	18.0

Hazardous road identification methods

Four assessment methods were used to compare the four HRL identification techniques in this section. The identification techniques include CF, CR, EB adjustment and PSI methods. The assessment methods include the SCT, TRDT, MCT and TST.

Crash frequency method

CF is the simplest and most common method for identifying HRLs (Hu et al., 2021; Persaud, 2001; Tarko and Kanodia, 2004). This method ranked the roadway segments of the recorded CFs in descending order. The safety of the roadway segments of different lengths was compared by dividing the total number of crashes by the section length. Therefore, the site with the highest number of crashes per km received the highest ranking.

Crash rate method

The number of crashes is divided by the traffic volume and the segment's length, which gives the CR. This study measured CR as the number of crashes per vehicle km for the study period. The data on crash history and traffic volume covered the period from 2010 to 2012 as the first period and from 2013 to 2015 as the second period.

Empirical Bayes method

The EB method was used to account for the RTM bias found in the road crash datasets to improve the accuracy of road safety estimation. This method helps combine observed crashes with predicted crashes (derived from CPMs) to obtain more accurate results in the estimation of expected crashes at each location. Therefore, this method was utilised to determine the predicted crash and weight adjustment factor for each location within the study area. The general function to calculate expected crashes using the EB method is defined in detail by Equation (3) (AASHTO, 2010):

$$N_{exp.,i} = \omega_i \times N_{pre.,i} + (1 - \omega_i) \times N_{obs.,i} \tag{3}$$

The values of the weighting factor (ω) range between 0.0 and 1.0, where ω is calculated as follows:

$$\omega_i = \frac{1}{1 + k/L_i \times \sum_{t=1}^{T} N_{pre.i}} \tag{4}$$

where: $N_{exp,i}$ – expected crashes at i roadway segment; ω_i – weighting adjustment to model prediction; $N_{pre,i}$ – predicted crashes at i roadway segment in a time t (year); $N_{obs,i}$ – the observed crashes at i roadway segment; k – parameter of over-dispersion of the prediction model; and L_i – length (km) of roadway segment. The over-dispersion parameter (k) reflects the degree of systematic variation in CFs that the model cannot explain for. The over-dispersion parameter will have a value of zero when the predicted model explains all systematic variations in the crash frequencies (Elvik et al., 2017). In such cases, the value of ω will be equal to 1.0. For applying the EB adjustment method, model I was chosen to calculate the predicted crashes for roadway segments based on the GOF results. Thereafter, the weighting adjustment factor (ω) was estimated using the over-dispersion value ($k = 0.580$, for the developed model) and the predicted crashes utilising the data for the first three years (2010–2012).

Potential for safety improvement method

The PSI value was determined by calculating the difference between predicted and expected accidents at a certain location. The computed PSI value for each highway segment within the research region was used to identify the HRLs in this study. A significantly positive PSI value implies that there is a need for safety improvements and vice versa.

Evaluation of methods

The SCT, TRDT, MCT and TST were used for evaluation. SCT accesses the ability of the HRL identification method to consistently identify a site as having a high crash risk over consecutive periods. The test assumes that a site identified as a high risk site during a certain period (i) should also reveal inferior safety performance in the next period ($i+1$), because there is no requirement for safety treatments at those sites (Cheng and Washington, 2008; Cheng and Washington, 2005). The more accurate the HRL identification process, the more sites with a higher SCT value will be chosen. The SCT values can be computed as follows:

$$\mathrm{SCT}_j = \sum\nolimits_{k=n-n\alpha}^{n} C_{k,method=j,i+1} > \sum\nolimits_{k=n-n\alpha}^{n} C_{k,method\neq j,i+1} \tag{5}$$

where: n –number of the segments being compared ($n = 80$); C_k – crash count for segment ranked k; α – threshold of high-risk segments identified (e.g., $\alpha = 0.10$ corresponding with top 10 % of n segments identified as HRLs); j – HRL identification method being compared; and i – observation period (e.g., i = first period from 2010 to 2012 and $i+1$ = second period from 2013 to 2015).

The TRDT considers the sites' safety performance rankings in the two consecutive periods. The test was carried out by computing the total rank differences between the two time periods (Montella 2010). The lower the TRDT score, the more likely the site is to be identified as an HRL. The test values can be computed as follows:

$$TRDT_j = \sum_{k=n-n\alpha+1}^{n} \left|\Re(k_{j,i}) - \Re(k_{j,i+1})\right| \tag{6}$$

where: $\Re$ – the rank of segment k in period i for method j.

The MCT measures the number of the same HRLs identified in two consecutive time periods. The test assumes that highway portions have the same traffic conditions, geometric design, and driver population in both periods. Under this homogeneity assumption, the greater the number of HRLs identified in both periods, the more consistent the method's performance. The MCT test statistics are shown in Equation (7) (Cheng and Washington, 2008):

$$MCT_j = \{k_{n-n\alpha}, k_{n-n\alpha+1}, \cdots, k_n\}_{j,i} \cap \{k_{n-n\alpha}, k_{n-n\alpha+1}, \cdots, k_n\}_{j,i+1} \tag{7}$$

where: k –segment being compared between two consecutive time periods, that is from i to $i+1$.

The results of the SCT, TRDT, and MCT evaluation criteria are then merged using TST to provide a synthetic index. The TST test assumes that all effectiveness tests have equal weight. In numerical form, the TST test statistics are shown in Equation (8) (Montella 2010):

$$TST_j = \frac{100}{3} \times \left[\left(\frac{SCT_j}{max_j SCT}\right) + \left(1 - \frac{TRDT_j - min_j TRDT}{max_j TRDT}\right) + \left(\frac{MCT_j}{max_j MCT}\right)\right] \tag{8}$$

where: max_jSCT, max_jTRDT, and max_jMCT –the largest values obtained from method j; min_jTRDT –the smallest value obtained from method j. A greater TST value (closer to 100) is the preferable method j.

Evaluation results and discussion

This evaluation identified the top 10 % and 15 % of the segments as hazardous segments with PSIs. Table 5 presents the evaluation results of four HRL identification methods based on SCT, TRDT, MCT and TST evaluation criteria. For the SCT criterion, the CF method outperformed the EB adjustment and PSI methods in the top 10 % of sites, while the EB adjustment method outperformed the others in the top 15 % of sites. The CR method performed significantly worse than the other methods in both the top 10 % and 15 % of sites, with the identified sites having the lowest crash frequencies per km in the second period. In the case of the TRDT criterion, the EB adjustment method outperformed the other methods, while the CR method performed the worst (i.e. greater the total rank differences) in identifying the top 10 % and 15 % of sites. Similar outcomes were obtained with the MCT (i.e. MCT=2 sites) for both the EB adjustment and the CF methods with respect to the top 10 % sites, whereas the CF method outperformed other methods by identifying five sites in the first period that were also identified as hazardous sites in the second period with respect to the top 15 % sites.

Overall, it is observed that the EB adjustment method performed better than the CF and PSI methods and that the CR method performed the worst in terms of the TST criterion with respect to the top 10 % and 15 % of sites. These results are consistent with the results obtained by Cheng and Washington (2008) and Montella (2010). However, it is not

Table 5
A comparison of the four methods for locating HRLs.

Method		α = 0.90				α = 0.85			
		SCT [a]	TRDT	MCT	TST	SCT [a]	TRDT	MCT	TST
EB	Test result	51.4	186	2	99.2	71.9	307	4	93.3
	Test ranking	*2*	*1*	*1*	***1***	*1*	*1*	*2*	***1***
CF	Test result	52.7	239	2	95.1	66.3	400	5	90.8
	Test ranking	*1*	*2*	*1*	***2***	*2*	*2*	*1*	***2***
PSI	Test result	49.9	292	1	71.8	65.8	449	3	73.8
	Test ranking	*3*	*3*	*2*	***3***	*3*	*3*	*3*	***3***
CR	Test result	28.3	362	1	51.7	50.3	470	3	65.1
	Test ranking	*4*	*4*	*2*	***4***	*4*	*4*	*3*	***4***

Note: α = 0.90 and α = 0.85 represent the cases of top 10 % and 15 % hazardous roadway segments.
[a] SCT results are based on the observed crashes per kilometre in the second period (2013–2015).

surprising that the EB adjustment method, which takes into account the RTM bias through estimates of the expected crash frequencies for each roadway segment, produces better results than the other methods for identifying HRLs. In contrast, the CR method consistently demonstrated the worst against all criteria. This conclusion is concerning because many road agencies use the CR method for its simplicity in identifying HRLs.

Table 6 displays the top 15 % (12 locations) of HRLs identified using EB method, which was determined to be the most effective method based on the previous compression results (refer to Table 5). The findings identify RS-43 the hazardous segment. This particular segment has an undivided four lanes, with two lanes in each direction, on flat profile (grade = 0), no road shoulders, and a speed limit of 60 kph. The study recommends several treatments for this poorly performing segment, including reducing the speed limit by 10 kph, adding a median island, and increasing lane width. Previous studies (Abdel-Aty and Radwan, 2000; Ackaah and Salifu, 2011; Al-Marafi, 2019; Al-Marafi and Somasundaraswaran, 2023; Pew et al., 2020) guided the assessment of the safety impact of these recommended treatments.

Table 6
Top 15% of HRLs identified using the EB method.

Segment ID	Length (km)	Observed crashes/ 3yr	Predicted crashes/ 3yr	Weight factor (ω)	EB estimated	EB rank
RS-43	0.29	6	2.30	0.19	5.31	1
RS-4	0.74	5	2.70	0.33	4.24	2
RS-72	0.41	5	1.97	0.27	4.17	3
RS-16	0.90	5	2.53	0.39	4.03	4
RS-19	0.40	4	2.56	0.22	3.68	5
RS-53	0.27	4	2.21	0.18	3.68	6
RS-8	0.46	4	2.40	0.26	3.59	7
RS-32	0.78	4	2.68	0.35	3.54	8
RS-42	0.25	4	1.69	0.21	3.51	9
RS-21	0.78	4	2.49	0.36	3.45	10
RS-49	0.42	4	1.98	0.28	3.44	11
RS-6	1.00	4	2.37	0.43	3.30	12

Conclusions and recommendations

When road agencies have financial constraints, for example, they can only examine and treat a limited number of sites, therefore, ranking HRLs is critical. The primary goal of this study was to assess the most commonly used ranking methods for detecting HRLs using real crash data. This study evaluated four ranking methods, including CF, CR, EB adjustment and PSI method, utilising the following statistical tests: SCT, TRDT, MCT, and TST. To accomplish this task, CPMs with NB structures were initially developed based on crash data obtained from 80 roadway segments in Toowoomba city, Australia. Several GOF assessments were applied to the predicted models to show the performance of each model. One of the examined models was proved to be highly statistically significant. The identified model was used to estimate the predicted and expected crash frequencies required, especially for the EB adjustment and PSI methods.

Results show that the EB adjustment method outperformed in most evaluation tests, ranking in the top 10 % and 15 % of hazardous segments. Therefore, the study concluded that the EB adjustment method is considered to be one of the most logical and reliable methods for ranking HRLs. In contrast, the CR method consistently performed the worst. The reason for this may be that the CR method favours low-traffic volume sites and implicitly assumes that CRs follow a linear relationship with traffic volume, whereas several other studies (Bonneson and McCoy, 1993; Lord et al., 2005; Park and Abdel-Aty, 2016) have confirmed that this relationship is often nonlinear. This result is quite concerning because many road agencies use the CR method.

The study also acknowledges that the benefits of the EB modification method were derived only through the use of severe-crash data from Toowoomba, Australia, but the findings are significant and consistent with the findings of previous studies. In order to further strengthen confidence in the use of the EB adjustment approach and its advantages and benefits, future studies can be reproduced using all crash severity levels across a wide range of locations.

CRediT authorship contribution statement

Mohammad Nour Al-Marafi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kathirgamalingam Somasundaraswaran:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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