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Identification of High-Risk Intersections in an Urban Street Network Using Local and Highway Safety Manual Crash Prediction Models

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Abstract: Nowadays, highway safety is a vital issue because vehicle crashes cause tremendous human, economic, social, and environment losses. This study asses intersections' safety performance in Sulaimani urban street network where the number of vehicles has been rapidly growing, as the case study. Crash prediction models were developed and applied to assess the safety performance of the intersections. The crash data were reported from Sulaimani traffic police station, happened from January 2020 to September 2024. Besides the crash prediction models mentioned in the Highway Safety Manual (HSM), local crash prediction models for each selected intersections were developed, then the models were used as tools for assessing intersections safety performance. To know the intersections risk levels, five safety performance approaches were used namely Level of Safety Service, Excess Porengicted Average Crash Frequency using Safety Performance Function, Expected Average Crash Frequency with Empirical Bayes (EB) Adjustment, Equivalent Property Damage Only with EB Adjustment, and Excess Expected Average Crash Frequency with EB Adjustments. The results indicate that the local prediction model has a higher R^2 than the HSM model, indicating a better fit to the local traffic and road conditions specifically at four-leg signalized intersections, the local model achieved an R^2 value of 0.618, which is substantially higher than the 0.208 obtained from the HSM models. Moreover results show that four-leg signalized intersections have significantly higher crash rates, with 15 intersections identified as high-risk across both models. The findings offer practical insights for prioritizing safety improvements and resource allocation to enhance traffic safety in urban areas.

1. Introduction

Urban intersections are nodes within urban street networks where vehicle movements frequently conflict with each other and other road users, often leading to increased crash risks [1]. As cities grow and traffic volumes increase, understanding and mitigating the crash risks associated with intersections become a primary objective in traffic safety researches. Predictive modeling serves as a beneficial tool for proactive safety planning, allowing transportation engineers to estimate expected crash frequencies based on traffic parameters, geometric design features, and other site-specific and traffic exposure factors [2]. Generally, traffic safety can be assessed by using two main methods: reactive and proactive analyses. Using reactive analysis methods for safety assessment involves evaluating locations based on actual crash data, while proactive assessment methods evaluate the locations based on analyses before crashes occur [3].

Proactive assessment analysis methods are particularly valuable in urban environments undergoing rapid growth, such as Sulaimani city, where preemptive engineering and management planning can substantially reduce crash frequencies. This forward-looking approach enables traffic engineers and planners to identify high-risk locations rather than waiting for crashes to occur. One of the most influential parameters in such proactive assessment analysis methods is Average Annual Daily Traffic (AADT), which is used as a variable for developing crash prediction models [4, 5].

To assess the safety performance in this study, five key approaches were utilized: Level of Safety Service (LOSS), Excess Predicted Average Crash Frequency using SPFs (EPACFspfs), Expected Average Crash Frequency with Empirical Bayes Adjustment (EACFEB), Equivalent Property Damage Only Average Crash Frequency with EB Adjustment (EPDOEB), and Excess Expected Average Crash Frequency with EB Adjustments (EEACFEB). Collectively, the approaches provide robust analyses to identify high-risk intersections by comparing observed crash data to predicted values, considering traffic volume, crash severity, and site characteristics. The LOSS approach offers an intuitive safety performance assessment; however, it is somewhat limited by potential regression to the mean (RTM) effects. EPACFspfs and EACFEB approaches improve safety predictive accuracy through SPFs and EB techniques, respectively. Particularly, the Empirical Bayes (EB) is effective in adjusting the RTM bias. The EPDOEB approach incorporates crash severity using weighted scores, although it may overstate locations with few severe crashes. The EEACFEB approach refines site prioritization by indicating locations with crash frequencies significantly above expectations. Together, these approaches enhance traffic and planning decision-makers to prioritize the high crash locations to be treated [6].

Four crash predictive equations were modeled for the selected intersections and then they were used to obtain predicted crash frequencies. On the other hand, the predicted crash frequencies for the selected intersection were obtained based on the Highway Safety Manual (HSM) prediction model. Both sets of models were utilized for finding the most dangerous intersections based on the mentioned safety performance function approaches in the HSM.

The remaining sections are organized as follows: section 2, Related Works, explores previous research on crash prediction and intersection safety. Section 3, Materials and Methods, describes the study area, the data used, and how both the local and HSM models were applied. Section 4, Results, presents the main findings of the analysis, followed by section 5, Discussion, which offers an interpretation of the results in the local context. Finally, section 6, Conclusions, presents the key findings of the study, including model performance and the identification of high-risk intersections.

2. Related Works

To enhance safety issues and reduce the number of crashes at street networks, several researchers studied safety of intersections in urban and suburban cities. Guo *et al.* [7] studied 170 signalized intersections in Florida using Bayesian models considering spatial correlations along street corridors. It was obtained that nearby intersections shared similar crash patterns due to shared traffic flow and design features. The Poisson spatial model provided the best fit, and factors like intersection size and signal coordination had a significant impact on intersections' safety, they also found that ignoring the relationships between nearby intersections can underestimate crash risk.

Furthermore Zhu *et al*. [8] developed a comprehensive intersection safety evaluation model based on weighted conflict points per unit area, adjusted by geometric design and safety facility factors. Unlike traditional approaches, the model did not require crash data or conflict observation. A practical tool for proactive safety assessment was offered by cooperating objective weights for conflict severity and correction factors; they also found that this method could effectively identify potentially dangerous intersections even before crashes happen.

Additionally Sobhani *et al.* [9] proposed a Safety Analysis CHain framework to assess intersection safety by modeling five stages: traffic flow, conflicts, conflict severity, crashes, and crash severity. Using traffic simulation and severity models, two key indicators were introduced: Casualty Crash Risk of a

Maneuver (CCRM) and Danger Index for a Maneuver (DIM). The method enabled proactive evaluation of intersection safety and comparison of different designs and results showed their method works well for early safety checks.

To allocate resources for safety improvements at urban intersections over a multiyear period, Mishra and Khasnabis [10] optimized an intersection safety model. The model utilized integer programming to maximize crash cost savings, taking considering budget and policy constraints into account. The model was applied to the intersections in Detroit, where crash-related losses exceeded $4 billion annually. The approach supported strategic and flexible investment planning for intersection safety and they found it useful for making better safety plans with limited budgets.

Furthermore, Kweon and Lim [11] analyzed crash data from 18,356 intersections in Virginia to identify the most suitable models for safety analysis. It was obtained that panel data models (with or without time correlation) and pooled cross-sectional models provided the most reliable safety performance estimates. In contrast, simple cross-sectional models were less effective safety evaluations because they underestimated crash variability.

Similarly, Cheng *et al.* [12] developed a pedestrian Safety Conflict Index model to quantitatively assess safety at signalized intersections involving pedestrian-vehicle conflicts. Key factors influencing the conflicts were identified, and a safety level classification system was proposed. The model was tested in Changchun, China, and showed reliable results, supporting its application in pedestrian safety evaluation; their tool helped rank intersections by safety level and was accurate in tests.

In 2014, pedestrian crash prediction models were developed by Haghighatpour and Moayedfar [13]. Twenty signalized intersections in Tehran were utilized for linear regression, Poisson, and Negative Binomial models. The study resulted that the Negative Binomial model was the most reliable model due to over dispersion of the data. Key factors influencing pedestrian crashes were identified and validated using statistical tests and sensitivity analyses. The models were appropriate to improve planning and pedestrian safety at urban intersections, providing reliable results to support better planning.

Barbosa *et al.* [14] developed Safety Performance Models (SPMs) for urban intersections in three Brazilian cities using variables such as AADT and number of lanes. A structured calibration method aligned with the HSM was followed. Despite challenges like insufficient data integration and crash location accuracy, the models showed appropriate transferability between cities. The study highlights SPMs development potential in developing countries, showing the models could work well in different cities.

In line with this ,Tay [15] employed a random parameters probit model to compare crash characteristics at urban and rural intersections in Alberta, Canada. Results illustrated that urban crashes were linked to wet roads, hit-and-runs, and high-traffic areas, while rural crashes involved higher speeds, more severe injuries, and run-off-road incidents. Necessity for area-specific countermeasures to improve intersection safety was highlighted and also showed that safety solutions should match the location type.

Additionally, Xu *et al.* [16] in Hong Kong, used a two-step Heckman selection model to estimate crash rates and severity at 262 signalized intersections. The method combined probit and regression modeling based on intersections traffic, design, and crash data. Results confirmed the importance of modeling crash rate and severity simultaneously for better safety evaluation as this gave more complete safety results.

In 2018, Essa and Sayed [17] analyzed six signalized intersections in Canada using video data to develop safety performance functions at the signal cycle level. Generalized linear models were utilized to link rear-end conflicts with traffic volume, queue length, shock wave features, and platoon ratio. The models were statistically significant and well-fitted. The used approaches enabled real-time safety improvements by adjusting signal timings, their model helping improve signal timing to make roads safer.

Similarly, Cai *et al.* [18] proposed a grouped random parameters multivariate spatial model to analyze crashes at road segments and intersections. The model included both zonal factors and site-specific factors, capturing unobserved and spatial effects. It performed better than traditional models, showing that considering zonal influences improves crash prediction accuracy.

Sun *et al.* [19] evaluated the safety performance of Restricted Crossing U-Turn (RCUT) intersections in Louisiana. The study resulted that RCUTs significantly reduce crashes, with 100% reduction in fatalities, 41.5% in injuries, and 22.3% in property damage only crashes at RCUT intersections. The RCUT design improved safety by eliminating direct crossing and left-turn movements from minor roads; therefore, RCUT designs made intersections safer.

In 2019 in China, Wang *et al*. [20] proposed a group-based signal timing optimization model for signalized intersections with mixed traffic flows, addressing both safety and delay. A probabilistic approach with a novel safety indicator (post-encroachment time × kinetic energy) was utilized to assess conflict severity. The model, which solved via a Nondominated Sorting Genetic Algorithm, showed a positive result of improving safety and efficiency over traditional signal control methods; it improved both safety and traffic flow.

In Regina, Canada, Park *et al.* [21] applied a Multiple Membership Multilevel Model to analyze five years of intersection crash data using both micro- (e.g., traffic volume) and macro-level (e.g., population) factors. The Multiple Membership Multilevel Model handled boundary zone effects and reduced errors obtained from traditional models. It provided more accurate crash predictions compared to single-level and conventional multilevel models.

Finally, Wang *et al.* [22] developed a novel real-time risk evaluation model for vehicle–pedestrian interactions, focusing on dynamic driver-pedestrian interaction preferences and defining "driving risk index" and "driving risk gradient." The model, which was calibrated with trajectory data from three intersections, outperformed traditional surrogate safety models like Time to Collision by better capturing complex and dynamic risks. Results showed an improvement in accuracy and continuity in risk assessment; this approach provides more detailed and accurate safety results than previous methods, supporting safer vehicle navigation and autonomous driving applications.

In Sulaimani city, traffic safety research has largely been limited to reactive approaches that rely on historical crash data; to the best of the authors' knowledge, no previous studies have applied crash prediction models to intersections. Previous studies have rarely focused on intersections, and none have incorporated predictive models. This study therefore represents the first effort in this field, providing a baseline for future research and practical applications in regional traffic safety management, by employing only predictive methods, specifically, a locally calibrated model and the HSM approach to evaluate safety conditions at 40 urban intersections. This represents a novel application of predictive modeling in a relatively large-scale urban network within the Sulaimani context. Table 1 summarizes related studies, outlining their datasets, methods, and key findings.

Table 1: Summarized related works.

Ref. No.	Year	Location / Dataset	Method / Model Used	Key Findings
[6]	2009	170 signalized intersections in Florida	Bayesian models considering spatial correlations	Nearby intersections shared similar crash patterns due to shared traffic flow and design features; Poisson spatial model provided the best fit.
[7]	2010	—	Weighted conflict points adjusted by geometric design and safety facility factors	Did not require crash data or conflict observation; offered a practical tool for proactive safety assessment.
[8]	2010	— (Monash University)	Safety Analysis CHain framework with simulation and severity models	Introduced CCRM and DIM; enabled proactive evaluation and comparison of intersection designs.
[9]	2012	Intersections in Detroit	Integer programming for safety investment planning	Crash-related losses exceeded $4 billion; supported strategic and flexible investment planning.
[10]	2012	18,356 intersections in Virginia	Panel data models, pooled cross-sectional, simple cross-sectional models	Panel and pooled models were more reliable; simple cross-sectional models underestimated crash variability.
[11]	2014	Signalized intersections in Changchun, China	Pedestrian Safety Conflict Index model	Identified key factors and proposed a safety level classification system; showed reliable results.
[12]	2014	20 signalized intersections in Tehran	Linear regression, Poisson, and Negative Binomial models	Negative Binomial model was most reliable due to over dispersion; validated key factors with statistical tests.

Table 1: Continue

[13]	2014	Urban intersections in three Brazilian cities	Safety Performance Models using AADT and number of lanes	Aligned with HSM; showed appropriate transferability despite data integration challenges.
[14]	2015	Alberta, Canada	Random parameters probit model	Urban crashes linked to wet roads and high traffic; rural crashes had higher severity and speeds; emphasized area-specific countermeasures.
[15]	2017	262 signalized intersections in Hong Kong	Two-step Heckman selection model (probit + regression)	Confirmed importance of modeling crash rate and severity simultaneously.
[16]	2018	Six signalized intersections in Canada	Generalized Linear Models with video data	Linked rear-end conflicts with volume, queue length, shock waves, and platoon ratio; enabled real-time signal timing safety improvements.
[17]	2018	—	Grouped random parameters multivariate spatial model	Showed improved prediction accuracy by including zonal and site-specific factors.
[18]	2019	Louisiana	— (RCUT evaluation)	RCUTs reduced fatalities by 100%, injuries by 41.5%, and property damage only crashes by 22.3%; improved safety by removing direct crossings and left-turns.
[19]	2019	Signalized intersections with mixed traffic flows	Group-based signal timing optimization, post-encroachment time × kinetic energy	Showed improvement in safety and efficiency using genetic algorithm-based signal control.
[20]	2020	Regina, Canada	Multiple Membership Multilevel Model	Handled boundary zone effects; more accurate crash predictions than tradition

3. Materials and Methods

To evaluate crash risks of urban intersections in Sulaimani city by developing crash predictive models and comparing them with the outcomes of HSM prediction approaches, three types of data were collected: crash, traffic, and geometric data.

3.1. Crash Data

A database was organized in which the characteristics of the crashes were arranged. The crash data were obtained from the reports of traffic police offices that cover all the crashes occurring from January 2020 to September 2024 period. The documented crash data reports included more than 56 urban intersections inside Sulaimani city; the dataset consists of 15 columns with detailed information on crash characteristics and site conditions. Key variables include time, day of week, accident type, road surface and weather conditions, lighting condition, accident severity, driver demographics (e.g., gender, age, seat belt use), and intersection type. This richness allows for comprehensive safety performance assessment .

Among the documented crash database , 40 intersections, as shown in figure 1, were selected for crash prediction modeling. The 40 intersections were investigated and categorized by traffic control device type and geometry. Specifically, the intersections included 15 four-leg signalized intersections, 14 four-leg Two Way Stop Control (TWSC) intersections, four three-leg signalized intersections, and seven three-leg TWSC intersections. The selected intersections were ranked from the highest to the lowest crash frequency.

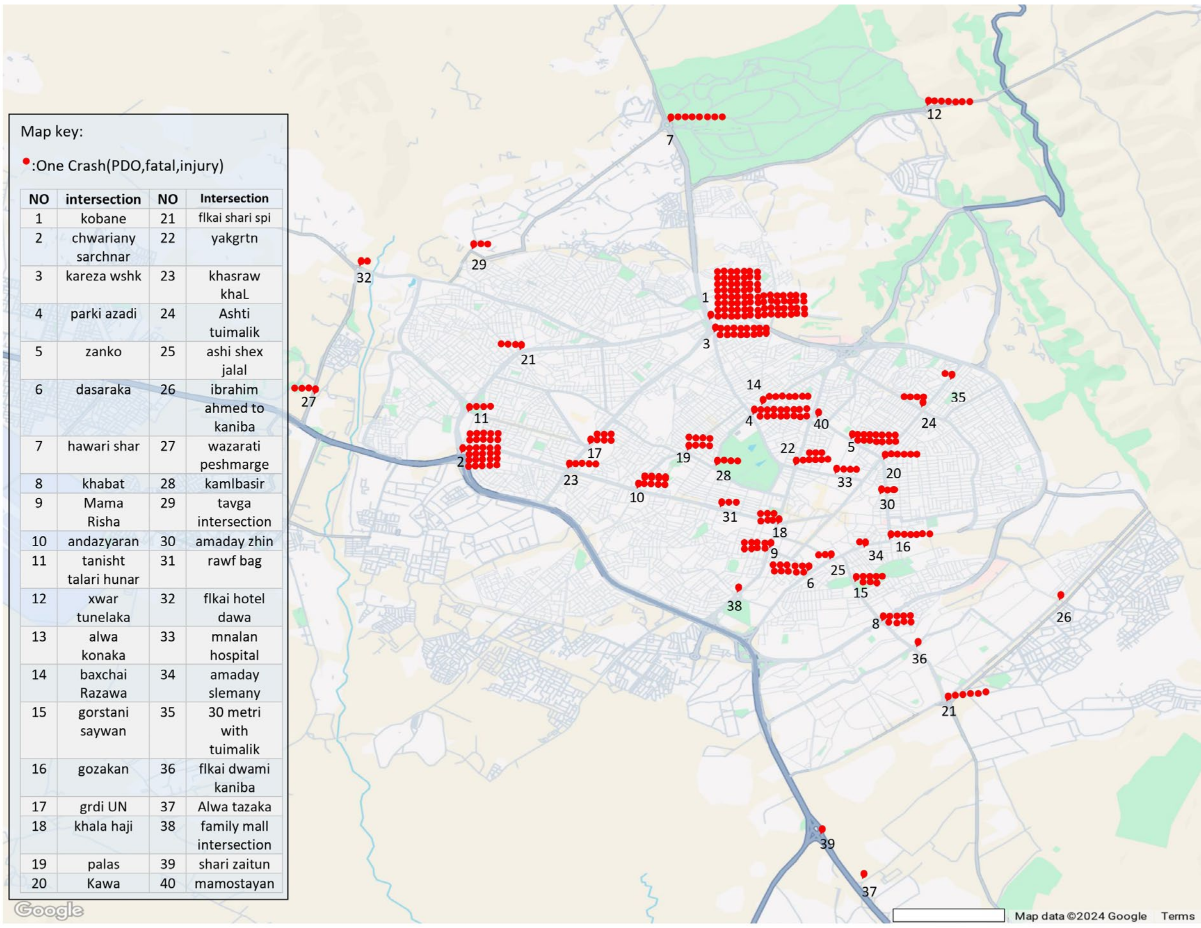

Figure 1: Map showing the frequency of crashes at studied intersections in Sulaimani city. The number of symbols corresponds to the number of crashes observed at each location during the study period.

3.2. *Traffic Volume Data*

Traffic volume data were collected by using video camera techniques for more than two hours for each of the 40 intersections during traffic congested hours. Peak hours were selected from each of the recorded traffic volumes of the intersections. Then the intersections' peak-hour traffic volumes were converted to AADT. In addition traffic control devices for intersection were investigated especially whether the intersection is signalized or TWSC.

3.3. *Geometric Data*

Geometric data including number of legs, and number, width, and configuration of lanes were collected through site investigations and satellite image from Google Earth.

3.4. *Crash Prediction Modeling*

Four predictive crash frequency formulas were modeled using multi-nonlinear regression in SPSS statistical software program for 4-leg signalized, 4-leg TWSC, 3-leg signalized, and 3-leg TWSC intersection types. These models were selected due to the availability of data and the high number of crashes observed at this type of intersections. The predictive crash frequency models were obtained from the SPSS program using multiple iterations. These models account for local traffic controls at urban intersections in Sulaimani city and were selected based on the availability of relevant data.

3.5. *HSM Application*

On the other hand, the HSM predict models were independently used to find predicted crash frequencies of the selected intersections. After finding the predicted crash frequencies by utilizing local and HSM models, the predicted crash frequencies were used in HSM approaches to assess the safety performance of the intersections, only proactive approaches were used, specifically five methods out of the 13 available approaches.

3.6. Safety Performance Evaluation

Five approaches were used for assessing intersections' safety performance namely: LOSS, EPACFspfs, EACFEB, EPDOEB, and EEACFEB. Based on the results of the mentioned crash predictive models and approaches, the most dangerous intersections were highlighted for further study and improvement

4. Results

The results of the multi non-linear regression models are shown in table 2**.** in which both locally developed crash prediction models and HSM models for different intersections' types are compared. Both types of local and HSM models are in the same mathematical forms, in which x_1 and x_2 are AADTs for major and minor approaches. The local models have higher R^2 than the HSM models; for example, at 4-leg signalized intersections the R^2 for the local model is 0.618 while for the HSM models is 0.208. The results emphasize the improved accuracy of locally calibrated models in reflecting regional traffic conditions and crash patterns. The local models can be used to assess the intersections' safety in the next step.

Table 2: Local and HSM multi-nonlinear models.

Type of intersection	Models	Model Equations	R2
4-leg signalized	Local	$y = e^{-157.543-33.105\, ln\, x_1+49.571\, ln\, x_2}$	0.618
	HSM	$y = e^{-10.21-0.68\, ln\, x_1+0.27\, ln\, x_2}$	0.208
4-leg TWSC	Local	$y = e^{1-0.34\, ln\, x_1-0.258\, ln\, x_2}$	0.258
	HSM	$y = e^{-5.33-0.33\, ln\, x_1+0.12\, ln\, x_2}$	0.002
3- leg signalized	Local	$y = e^{1-0.223\, ln\, x_1+0.739\, ln\, x_2}$	0.98
	HSM	$y = e^{-9.02+0.42\, ln\, x_1+0.4\, ln\, x_2}$	0.006
3-leg TWSC	Local	$y = e^{1.248-0.574\, ln\, x_1+0.464\, ln\, x_2}$	0.256
	HSM	$y = e^{-6.81+0.16\, ln\, x_1+0.51\, ln\, x_2}$	0.12

Table 3 shows the results of assessment of four-leg signalized intersections using the five mentioned methods. The most dangerous intersections were highlighted with red color, and the less dangerous intersections were highlighted with orange color. The LOSS results show that the local and HSM provide different safety assessment results; for example, the intersections of Chwariany Sarchnar, Parki Azadi, Zanko, Dastaraka, Khabat, Mama Risha, and Kawa can be indicated as high-risk intersections because they are in LOSS IV using local models. The same mentioned intersections can be indicated as moderate-risk intersections using the HSM model because they have lower LOSS score. Regarding EPACFSPFs approach, the critical value that is used as a boundary for separating high-risk from low-risk intersections should be greater than 2. Local model results show higher excessed scores than the results of the HSM model; for example, Chwariany Sarchnar, Parki Azadi, Zanko, and Dastaraka intersections are considered as high-risk intersections using the local model while they are not considered as high-risk intersections using the HSM model. Kobane intersection is the only one showing difference using the EACFEB approach, in which Kobane is considered as high-risk intersection using the local model while it is considered as moderate-risk intersection using the HSM model. The results of the scores are different using the EPDOEB approach for both models, but if the results of the assessment are considered, it can be said that there are slight differences among the results of assessment of the intersections. The only difference is Parki Azadi intersections, which is indicated as low-risk using the local model and it is indicated as moderate risk using the HSM model. Like the EPDOEB approach, there are no significant differences among the results of the EEACFEB approach using the local and HSM models. If both local and HSM models are considered, it can be said that Kobane and Chwariani Sarchnar are dangerous intersections and can be indicated for further analyses and safety treatment.

Table 3: Traffic safety assessment for 4-leg signalized intersections using local and HSM crash prediction models.

Name of Intersection	Models	LOSS	EPACFspfs	EACFEB	EPDOEB	EEACFEB
Kobane	Local	III	-0.33	13.11	380.13	362288.8
	HSM	III	5.37	4.33	333.41	301672.8
Chwariany Sarchnar	Local	IV	3.4	5.97	174.50	107963.3
	HSM	III	1.88	2.43	187.07	126349.8
Parki Azadi	Local	IV	3.71	0.19	80.58	1973.9
	HSM	III	1.18	1.33	102.40	38957.1
Zanko	Local	IV	3.16	0.00	57.77	0.0
	HSM	III	0.70	0.94	73.05	23558.1
Dasaraka	Local	IV	2.32	0.00	62.98	0.0
	HSM	III	0.66	1.07	82.22	30995.0
Khabat	Local	IV	1.89	0.00	157.31	0.0
	HSM	III	-0.21	1.72	130.88	-85411.3
Mama Risha	Local	IV	1.68	0.00	64.98	3.1
	HSM	III	-0.66	0.87	66.79	-6404.7
Gozakan	Local	III	1.47	0.00	151.99	0
	HSM	III	-1.91	0.94	72.77	-191774.9
Khasraw Khal	Local	III	1.05	0.00	39.46	0
	HSM	III	-2.83	0.46	35.65	-12574.3
Rawf Bag	Local	II	-1.59	0.00	74.33	-83.7
	HSM	II	-2.80	1.72	43.66	-76959.9
Kaml Basir	Local	III	-0.27	1.74	165.36	-83437.8
	HSM	III	-3.70	1.58	120.04	-211813.1
Yakgrtn	Local	III	-0.77	0.00	15.34	0
	HSM	III	0.70	0.68	14.19	-2846.1
30-Metri with Tui-malik	Local	III	-0.77	1.13	29.72	-12802.2
	HSM	III	-5.12	0.25	19.97	-158485.5
Flka Sawzaka (Mamo-stayan)	Local	II	-1.59	1.06	68.43	-53436.8
	HSM	III	-9.70	0.64	49.21	-106422.5
Kawa	Local	IV	0.21	0.00	78.95	0
	HSM	II	-2.55	0.25	20.49	-133328.6

The results of the safety assessment for the 4-leg TWSC intersections are illustrated in table 4. Regarding the LOSS approach, most of the intersections are in LOSS IV using the local model, while they are in LOSS III or II using the HSM model. Five intersections, namely Alwa Konaka, Baxchai Razawa, Palas, Flkai Shari Spi, and Ashti-Twi Malik, are indicated as moderate- risk using the local model with the EPACFspfs approach, as shown in the table 4. On the other hand, the same mentioned intersections are indicated as low-risk intersections using the HSM model. Generally, the local model results higher scores than the HSM model using EPACGspfs; for example, for Hawari Shar intersection, the score is 1.86 using the local model, while it is 0.16 using the HSM model. For the EACFEB approach, which adjusts for regression-to-the-mean bias, both models returned low absolute score values, but the HSM model approach shows consistently higher adjusted score values. Three intersections, namely Baxchai Razawa, Palas, and Flkai Shari Spi, are indicated as moderate-risk intersections using the HSM model, while none of the intersections are indicated as dangerous intersections using the local model. In terms of the EPDOEB approach, which reflects excess minor crashes, most of the intersections substantially have higher score values using the local model than the scores values using the HSM model. Regarding EEACFEB, only Hawari Shar intersection is indicated as high-risk intersection using HSM, while the same intersection is indicated as moderate-risk intersection using the local model. Considering all the used approaches with the two models, Hawar Shar and Baxchai Razawa intersections can be indicated as high crash locations for further investigations and engineering remedies.

Table 4: Traffic safety assessment for 4-leg TWSC intersections using local and HSM crash prediction models.

Name of intersections	Models	LOSS	EPACFspfs	EACFEB	EPDOEB	EEACFEB
Hawari Shar	Local	III	1.86	0.07	13.54	4245.8
	HSM	IV	0.16	0.97	34.30	52255.0
Alwa Konaka	Local	IV	1.46	0.03	69.74	-1180.3
	HSM	III	-1.15	1.87	28.59	-111194.7
Baxchai Razawa	Local	IV	1.47	0.01	174.92	-203.5
	HSM	III	-1.01	3.05	136.83	-113429.0
Palas	Local	IV	1.46	0.01	45.28	28.2
	HSM	III	-1.01	2.01	46.59	-5120.3
Flkai Shari Spi	Local	IV	1.26	0.01	28.70	-1622.9
	HSM	III	-2.69	2.23	6.32	-286253.8
Ashi Shex Jalal	Local	IV	0.83	0.01	84.6	-1341.4
	HSM	III	-3.18	1.42	18.13	-177030.8
Shoflu Hafarakani Tavga	Local	IV	-0.62	0.01	48.92	-1158.4
	HSM	III	-4.08	1.34	15.59	-89117.2
Flkai Hotel Dawa	Local	IV	0.42	0.01	117.54	-1158.4
	HSM	II	-4.79	1.54	19.41	-207919.8
Amaday Slemany	Local	IV	0.41	0.02	48.2	-1488.3
	HSM	II	-4.85	1.18	15.85	-86928.0
Flkai Duwami Kaniba	Local	IV	0.21	0.01	96.81	-1706.2
	HSM	II	-5.19	1.31	18.80	-207919.8
Ibrahim Ahmed to Kaniba	Local	III	0.83	0.72	79.32	-1786.5
	HSM	III	-2.83	1.39	18.54	-161428.5
Family Mall Intersection	Local	IV	0.2	0.01	58.46	-1333.2
	HSM	II	-7.19	1.14	16.28	-113744.9
Ashti Tuimalik	Local	IV	1.04	0.01	79.11	-95.4
	HSM	II	-2.88	0.82	62.96	-12574.3
Amaday Zhin	Local	IV	0.62	0.01	73.08	-1331.4
	HSM	III	-4.37	0.25	17.84	-146423.9

As with the 4-leg signalized and TWSC intersections, the LOSS approach resulted that the local model provides higher LOSS score values for all intersections of 3-leg signalized intersections, as shown in table 5. Based on the local model, all the intersections of Kareza Wshk, Andazyaran, Gorstani Saywan, and Grdi UN are high-risk intersections while they are moderate-risk intesctions using the HSM model. The results of EPACFspfs using the local model showed that Kareza Wshk intesction is indicated as high-risk intersection with a score value of 4.42. Andazyaran and Gorstani Saywan intersections are indicated as moderate-risk intersections using the same approach and model. On the contrary, the HSM model provided higher score values than the local model using the EACFEB approach; for example, Kareza Wsh and Andazyaran are indicated as high-risk intersections using the HSM model while both of them are low-risk intersctions using the local models. Using the EPDOEB approach with the local and HSM models, Andazyaran intersection is indicated as high and moderate-risk intersection with score values of 237.12 and 162.64, respectively. The results of using the EEACFEB approach indicate that only Kareza Wsh intersction is indicated as a dangerous intersection using the HSM model. If all the used approaches and models are considered, Kareza Wshk intersection can be indicated as a dangerous intersection.

Table 5: Traffic safety assessment for 3-leg signalized intersections using local and HSM crash prediction models.

Name of intersections	Models	LOSS	EPACFspfs	EACFEB	EPDOEB	EEACFEB
Kareza Wshk	Local	IV	4.42	0.001	85.61	21
	HSM	III	0.66	4.14	130.72	86012.9
Andazyaran	Local	IV	1.68	0.0004	237.12	-12.4
	HSM	III	-7.72	3.44	162.94	-201721.5
Gorstani Saywan	Local	IV	1.47	0.0004	57.03	0.6
	HSM	III	-1.02	2.01	57.20	-7341.4
Grdi UN	Local	IV	1.68	0.0008	163.79	-44.6
	HSM	III	-5.12	0.68	91.42	-185142.2

Table 6 shows the results of traffic safety assessment for 3-leg TWSC intersections using local and HSM crash prediction models. The results of LOSS approach using the local model provide that Wazarati Peshmarge is the only dangerous intersection with LOSS score IV. In contrast, HSM rated Wazarati Peshmarga intersection and all other intersections as LOSS III and II. Only Tanisht Talari Hunar intersection with a core value of 1.18 is indicated as high-risk location using EPACFspfs approach with the HSM model. The score values of using the local model are slightly higher than the score values using the HSM model. In terms of EACFEB with the HSM model, Xwar Twnelaka and Khala Haji intersections are indicated as high-risk intersections with score values of 2.36 and 2.06, respectively. In this approach, the HSM model tended to return slightly higher score values, indicating HSM's broader adjustment for RTM bias. Regarding the EPDOEB approach results, the local prediction model provides higher score values than the HSM model; for example, Shari Zaitun and Khala Haji intersections are indicated as high-risk intersection by using the local model while they are not indicated as high-risk intersections by using the HSM model. Lastly, the EEACFEB approach showed that Tanisht Talari Hunar is the only dangerous intersection using the HSM model. Overall, it can be said that Tanish Talari Hunar intersection is the most dangerous intersection among them.

Table 6: Traffic safety assessment for 3-leg TWSC intersections using local and HSM crash prediction models.

Name of intersections	Models	LOSS	EPACFspfs	EACFEB	EPDOEB	EEACFEB
Tanish Talari Hunar	Local	III	0.38	1.53	45.08	4245.8
	HSM	III	1.18	0.94	30.88	48778.6
Xwar Tunelaka	Local	III	0.45	1.2	92.97	-51727.8
	HSM	III	-4.08	2.36	78.49	-112593.0
Khala Haji	Local	III	0.37	1.31	103.01	-86276.7
	HSM	III	-4.70	2.06	76.09	-174424.8
Wazarati Peshmarge	Local	IV	0.48	0.51	65.36	-53341.1
	HSM	III	-3.18	1.41	19.04	-182084.3
Mnalan Hospital	Local	II	-0.41	0.63	17.35	-33512.7
	HSM	II	-1.15	0.83	12.75	-48490.7
Shari Zaitun	Local	II	-0.24	0.37	158.08	-163069.7
	HSM	II	-9.70	1.00	21.95	-542300.9
Alwa Tazaka	Local	II	-0.94	0.62	25.08	-70755.7
	HSM	II	-5.59	0.83	15.26	-105870.0

5. Discussion

This study revealed that locally developed crash prediction models outperform HSM models in evaluating intersection safety in Sulaimani. The higher R^2 values of local models demonstrate their superior accuracy, largely due to their ability to reflect local traffic patterns, driver behavior, and geometric conditions. This aligns with findings by Guo *et al.* [7], who demonstrated that accounting for spatial correlations and local intersection characteristics significantly improves the accuracy of crash prediction models at signalized intersections. These results further emphasize the importance of context-specific modeling approaches, as uncalibrated models may not account for regional traffic culture, roadway design practices, or enforcement conditions.

Comparative analysis across five safety performance approaches (LOSS, EPACFspfs, EACFEB, EPDOEB, and EEACFEB) consistently showed that local models identified more high-risk intersections. For example, intersections like Chwariani Sarchnar and Kareza Wshk were ranked as more hazardous by local models, while HSM models underestimated their risk, Sobhani *et al.* [9] highlighted that crash prediction models lacking local calibration may not accurately capture pedestrian crash risks at urban intersections, stressing the importance of incorporating local traffic and design characteristics.

The practical implication is that transportation agencies in rapidly growing cities like Sulaimani should develop and apply locally calibrated models to guide safety interventions effectively. By doing so, limited resources can be targeted toward intersections with the highest crash risk. This recommendation is supported by Mishra and Khasnabis [10], who emphasized that using locally specific crash data and tailored safety alternatives enables more effective prioritization and allocation of resources for safety improvements at urban intersections. Beyond resource allocation, locally based models can also support long-term planning, provide decision-makers with greater confidence in safety evaluations, and improve transparency in project selection. Overall, these findings demonstrate that while the HSM framework offers a valuable reference, its direct application without local calibration does not fully capture the realities of urban traffic in Sulaimani, and developing models responsive to local conditions provides a more sustainable foundation for data-driven safety management.

The study faced several limitations and challenges. The availability and quality of local crash and traffic data were limited, and some crash report forms were incomplete, containing missing or empty fields. Collecting video recordings was difficult, as stable camera records were often inaccessible due to security restrictions. Additionally, the names of intersections were inconsistent—some recorded by person names, others by location—which created confusion during data compilation. The predictive models developed in this study are specific to Sulaimani and may not be directly applicable to other cities without recalibration. Furthermore, certain factors influencing crashes, such as driver behavior or temporary road conditions, were not included due to lack of data.

This study is novel as it represents the first attempt to develop and compare crash prediction models for intersections in Sulaimani city, integrating both locally calibrated models and HSM approaches. The use of multiple evaluation methods, together with a rich dataset from crash records, traffic counts, and field surveys, strengthens the reliability of the findings. Importantly, the results are not only methodologically robust but also highly practical, as they identify priority intersections for safety improvements and contribute to the limited body of research from developing countries.

6. Conclusions

To assess the intersections in Sulaimani urban street network, four local crash predictive models were developed. The local models provide better safety performance assessment than the HSM crash prediction models because they represent the traffic flow and driver behavior characteristics in Sulaimani's urban street network. The local models resulted in higher scores for most of the used approaches than the HSM models. The intersections were highlighted and classified based on low, moderate, and risk intersections. If an intersection was highlighted as high and/or moderate-risk intersections for most of the used approaches, then this intersectionwas identified as the most dangerous intersection. Regarding the 4-leg signalized type, Kobane and Chwariani Sarchnar intersections were identified the most dangerous intersections. For 4-leg TWSC intersection type, Hawar Shar and Baxchai Razawa intersections were identified as high-risk intersections. Among the 3-leg signalized intersections, Kareza Wshk intersection was identified the most dangerous one. Lastly, Tanish Talari Hunar intersection was identified as a high-risk intersection among 3-leg TWSC intersection types. The selected most dangerous intersections can be prioritized for further investigation and study to be improved.

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