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Modelling Safety Performance Functions and Assessing Highway Safety Manual (HSM) Prediction Models for Four-Lane Undivided Arterials – A Case Study of Kathmandu District

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Abstract

Rapid urbanization in Kathmandu district has contributed to a significant rise in traffic volumes, which has contributed to an increase in crash rates, especially on urban arterial roads. This study evaluates the applicability of Highway Safety Manual (HSM) predictive models for local conditions through establishing Safety Performance Functions (SPFs) and calibrating them with crash data of fiscal years 2077/78 to 2079/80. A total of seven four-lane undivided arterial segments were chosen, and crash prediction models for multiple-vehicle and single-vehicle collisions have been generated using negative binomial regression model. Statistical parameters, including Akaike Information criteria (AIC), Mean Absolute Deviation (MAD), and Mean Prediction Bias (MPB), were used to assess the model's performance. Among all the crash prediction models developed, Model III had the lowest AIC value and better overall performance for both multiple vehicle and single vehicle collisions. Crash Modification Factors (CMFs) were used to adjust for deviations from the baseline conditions, and a local calibration factor was computed. The calibration factor of 0.53 was derived using observed and predicted crash frequencies. Afterwards, the 2080/81 crash data was used to evaluate the calibrated models. The obtained R^2 value of 0.6513 indicates a reasonable degree of model accuracy. The study concludes that jurisdiction-specific models with calibrated parameters significantly improve prediction accuracy and can be instrumental in guiding road safety initiatives in Kathmandu and other similar urban contexts.

Keywords: Highway Safety Manual (HSM), Predictive Models, Safety Performance Functions (SPFs), Local Calibration Factor, Crash Frequency, Road Safety, Crash Prediction

1. Introduction

1.1 Background

Road infrastructure is one of the indicators of a nation's development and hence its network in a country should be efficient and adequate (Bhattarai, 2019). But it is also the most problematic and complicated mode of transport in terms of safety for daily commuters. Road crash is the twelfth leading cause of death for all ages (World Health Organization, 2023) and also, the leading cause of death for children and young people aged 5-29 years. According to the latest statistics by WHO (2023), road crash fatalities and injuries affect 1.19 million and 20-50 million people per year respectively. The safety risks are three times higher in low-income countries than the high-income countries, where there are 9 deaths per 100,000 people on average (World Health Organization, 2023). In the case of Kathmandu district, urbanization and infrastructure development led to a significant increase in traffic volumes, which subsequently decreased the effectiveness of the road network and caused an alarming rise in crashes.

Traditional approaches to addressing the high-crash frequency sites, often known as reactive measures—such as enforcement of traffic police or the installation of basic traffic calming measures—often lack data-driven insights and fail to prevent crashes effectively. In contrast, predictive analysis, which identifies and analyzes patterns and trends in crash data, offers a more promising approach to reducing crashes. The Highway Safety Manual (HSM) provides a comprehensive framework for crash prediction through Safety Performance Functions (SPFs), which determine expected crash frequencies based on roadway attributes and traffic conditions. Data-driven techniques, like SPFs, can help develop effective road safety initiatives by understanding all relevant aspects (Mendes, Larocca, Silva, & Pirdavani, 2023). However, HSM models were primarily generated using data from USA, assessing the transferability of these models to local contexts is critical, especially in Nepal, where data availability is limited and no local SPFs exist. The HSM recommends calibration of the model to increase the accuracy and to get valid prediction results (AASHTO 2010). This study aims to calibrate SPFs for four-lane urban arterials and assess the applicability of HSM predictive models on urban arterials in Kathmandu district.

1.2 Scope of Study

This study aims at assessing how accurately HSM prediction models performs in predicting the frequency of crashes on four-lane undivided urban arterials in Kathmandu district. It includes developing SPFs and analysis of HSM models applicability in the area and calibrating them using local crash data.

To determine the accuracy and reliability, the study involves collecting and analyzing historical crash data, model calibration, validation, and performance evaluation. The findings will assist road safety experts, legislators, and transportation planners in enhancing the use of the model in the decision-making process and generating efficient safety measures for urban roadways.

1.3 Research Objectives

The main aim of this study is to determine the applicability of HSM predictive models in estimating crash frequency on four-lane undivided urban arterials in Kathmandu district. The specific objectives of this study are outlined as follows:

- To develop safety performance functions (SPFs) for Kathmandu district.
- To determine the calibration factor (C_r) for improving the predictive accuracy of HSM models using local crash data.

2. Literature Review

Due to the growing number of vehicles and the need for effective transportation, road crashes are, by far, the most common concern among economies worldwide (K.C., 2024). The development of urban infrastructure must prioritize road safety, and crash prediction models are essential for reducing the likelihood of crashes. Numerous techniques, such as the predictive models outlined in the Highway Safety Manual (HSM), have been developed to improve the accuracy of crash frequency estimation (AASTHO, 2009).

2.1 Models for Crash Prediction and HSM Techniques

Based on traffic volumes, traffic control features, and roadway design, the predictive method in Part C of the HSM (AASTHO, 2009) offers an organized method for estimating crash frequencies. Safety Performance Functions (SPFs), Crash Modification Factors (CMFs), and calibration factors are its three main components.

2.1.1 Safety Performance Functions (SPFs)

The average crash frequency for a given site type (under predetermined base conditions) is estimated using Safety Performance Functions (SPFs), which are regression equations that depend on annual average daily traffic (AADT) and, in the case of road segments, segment length (L). Base conditions are specified for each SPFs, which includes lane width, presence or absence of lighting, type of on-street parking, etc. SPFs are provided for multiple-vehicle non-driveway collisions and single-vehicle crashes (AASTHO, 2009).

2.1.2 Crash Modification Factors (CMFs)

CMFs account for geometric or geographic changes between the model's base state and the local conditions at the place under consideration. To account for the discrepancy between site conditions and designated base conditions, they are multiplied by the crash frequency forecasted by the SPF. CMFs, also referred to as countermeasures, interventions, actions, or alternative designs, are typically presented for the implementation of a specific treatment. In order to estimate the combined effects of the various elements or treatments, the predictive method makes the assumption that CMFs can be multiplied together.

2.1.3 Calibration factor (C_r)

Calibration is the process of updating SPFs to reflect varied crash frequencies across jurisdictions. The calibration factor accounts for discrepancies between the jurisdiction and period in which the predictive models were produced and the jurisdiction and period in which HSM users apply them. Calibration factors are used in the approach to ensure that the SPFs reflect actual local conditions.

The segment length (L) of a homogeneous roadway segment connecting two intersections is shown in Figure 1.

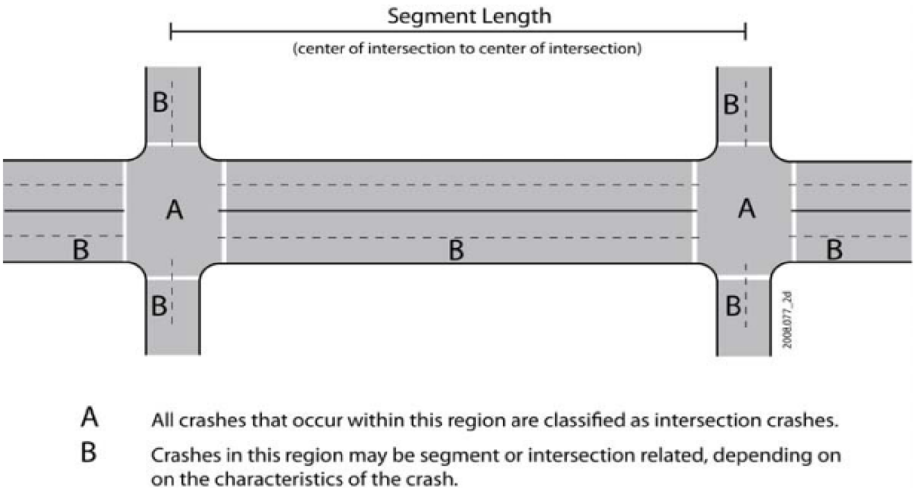

Figure 1: Definition of Roadway Segments and Intersections
(Source: (AASTHO, 2009))

SPFs and adjustment factors are provided for five types of roadway segments on urban and suburban arterials (AASTHO, 2009) which are given below:

- Two-lane undivided arterials (2U)
- Three-lane arterials including a center two-way left-turn lane (TWLTL) (3T)
- Four-lane undivided arterials (4U)
- Four-lane divided arterials (i.e., including a raised or depressed median) (4D)
- Five-lane arterials including a center TWLTL (5T)

The procedure addresses five types of collisions:

- Multiple-vehicle non-driveway collisions
- Single-vehicle crashes
- Multiple-vehicle driveway-related collisions
- Vehicle-pedestrian collisions
- Vehicle-bicycle collisions

2.2 Poisson's Regression Model

The Poisson regression model is the primary crash count model, as linear regression cannot handle non-negative data. The probability of identifying y_i crashes at road segment i is presented in (Equation *1*) (Lord & Mannering, 2010)

$$P(y_i) = \frac{exp(\mu_i)\mu_i^{y_i}}{y_i!} \quad \text{(Equation 1)}$$

where μ_i is the mean of crash counts at the segment i, which is the expected number of crashes, N_{SPFi}. It represents the function of crash contributing factors, X's that encompass traffic, geometric design, and other attributes with their corresponding coefficients (β), which are usually calculated using the maximum likelihood estimation (MLE) approach (Farid, Abdel-Aty, & Lee, 2019). The crash frequency prediction is defined in (Equation *2*) (Farid, Abdel-Aty, & Lee, 2019)

$N_{SPFi} = \exp(\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \ldots + \beta_p X_{pi})$ (Equation 2)

The Poisson model's shortcomings include incorrect findings for over-dispersed, low sample mean crash numbers, and under-dispersed data (Lord & Mannering, 2010).

2.3 Negative Binomial (NB) Regression Model

Crash data exhibits over-dispersion, meaning the variation exceeds the mean (Lord, 2006). The negative binomial (NB) model is a modification of the Poisson model that addresses over-dispersion in data (Lord & Mannering, 2010). The NB model is frequently implemented to predict crash frequency, and the HSM's SPFs follow this model. SPFs use negative binomial (NB) distributions, which are more suited for estimating count responses and dealing with over-dispersion (AASTHO, 2009) (Lord & Mannering, 2010). The mean function is configured in (Equation *3*).

$N_{SPFi} = exp(\beta X_i + \varepsilon_i)$ (Equation 3)

Where, X_i is a vector of explanatory variables, β is the vector of estimable parameters and $\exp(\varepsilon_i)$ is a gamma-distributed error term with mean 1 and variance α (Lord & Mannering, 2010). The addition of this term allows the variance to differ from the mean as $VAR[y_i] = E[y_i] \times (1 + k_i \times E[y_i])$ where k_i is over-dispersion parameter that allows NB model to accommodate over-dispersed crash data (Farid, Abdel-Aty, & Lee, 2019).

2.4 Transferability of HSM Predictive Model

Assessing previous research where SPFs developed for particular circumstances were employed elsewhere is just as crucial as pointing out the variety of statistical frameworks used for crash frequency predictions. In most of the previous research projects, the HSM calibration procedure was used to calibrate the HSM's default SPFs to particular jurisdictions. Turner (Turner, Persaud, Bassani, & Sacchi, 2011) illustrates that the HSM calibration procedure can be used as a procedure for transferring models across international boundaries; even from right-hand drive to left-hand drive countries. The HSM's SPFs were calibrated to rural two-lane two-way roadway segments of Utah (Brimley, Saito, Schultz, & Reese, 2011), Oregon (Xie, Gladhill, Dixon, & Monsere, 2011), Province of Turin (Sacchi, Persaud, & Bassani, 2012), Iran (Haghani, Jalalkamali, & Haghani, 2021), Brazil (Mendes, Larocca, Silva, & Pirdavani, 2023). For Utah's conditions, the researcher performs additional steps by developing new SPFs and comparing them to the calibrated HSM SPF. (Persaud, et al., 2012) estimated stop-controlled and signalized intersection SPFs for Toronto's conditions. (Ambros & Sedoník, 2016) evaluated the transferability of SPFs for divided and undivided highways in the Czech Republic (South Moravian region and Zlín region). The SPFs were calibrated to urban and suburban arterials of Alabama (Kim, Anderson, & Gholston, 2015), and statistical modelling was performed using jurisdictional crash data and NB regression model to develop Alabama-specific SPFs.

2.5 Previous Studies

Xie et al. (Xie, Gladhill, Dixon, & Monsere, 2011) highlighted important limitations in pedestrian volume data, minor road traffic volumes, and minimum sample sizes for collision analysis during an HSM calibration for Oregon highways. According to their findings, most calibration factors were below the predicted value of one, suggesting that reporting inaccuracies caused crashes to be underreported.

Wemple et al. (Wemple, Foster, & Bergh, 2010) used HSM's predictive method in a corridor planning project in the United States. The study showed that combining quantitative crash frequency projections with traffic operations and environmental evaluations can help inform safer highway design decisions. The study concludes that it is essential to consider site-specific interventions like implementing bicycle lanes, traffic signals and divided medians which contribute in reducing crash risks.

Mendes et al. (Mendes, Larocca, Silva, & Pirdavani, 2023) discovered that the calibration factors for all crash types and fatal/injury crashes were 2.62 and 2.35, respectively, indicating that the HSM model underestimated crashes. The study showed that Brazilian roadway characteristics, driver behavior, and crash patterns differ from those assumed in the original HSM models, highlighting the importance of calibrating the prediction models to local conditions, and also contributes to understanding the transferability of SPFs and how these models perform in atypical years (Mendes, Larocca, Silva, & Pirdavani, 2023). Furthermore, the research implies that developing jurisdiction-specific SPFs that are appropriate to local conditions would improve the model accuracy.

Turner et al. (Turner, Persaud, Bassani, & Sacchi, 2011) examined the feasibility of transferring crash prediction models across countries by comparing Safety Performance Functions (SPFs) from New Zealand, Australia, North America, Sweden, and Italy. Model transferability is possible between jurisdictions; however, differences in the model, such as reporting rates, design standards, speed environments, and climatic conditions, must be accounted for during transfer (Turner, Persaud, Bassani, & Sacchi, 2011). The study also highlighted the significance of conducting further research on the fundamental base models used in the HSM and validating these models before they are adopted for use worldwide.

Brimley (Brimley, Saito, Schultz, & Reese, 2011) calibrated SPFs of HSM for rural two-lane roads in Utah. The study uses negative binomial and hierarchical bayesian techniques to develop new SPFs. In order to improve forecast accuracy, the study recommended using locally tailored models after finding that the HSM SPF understated crash frequency by 16%.

Haghani et al. (Haghani, Jalalkamali, & Haghani, 2021) compared the performance of the HSM predictive model to the jurisdictional crash prediction model, which showed that the jurisdictional model had higher precision and lower bias compared to the HSM's model, and verified the transferability of the HSM's crash prediction model to a developing country. Despite limitations such as a small dataset and missing roadway parameters not present in the study area, the results showed that the calibrated HSM model can effectively identify high-risk segments and support safety improvements (Haghani, Jalalkamali, & Haghani, 2021). The study recommended future calibration for different types of roads and underscored the need to develop local crash modification factors to better address safety issues in developing countries.

Sacchi et al. (Sacchi, Persaud, & Bassani, 2012) investigated the transferability of the HSM algorithm to Italian two-lane undivided rural roads as a case study by comparing the HSM base model with a local model estimated on baseline conditions, and the transferability of the CMFs was then assessed. While some CMFs showed bias and the local SPF differed from the HSM base model, the methodology provides useful tools for jurisdictions worldwide to assess and improve HSM predictions (Sacchi, Persaud, & Bassani, 2012). The study suggests that for Europe, local SPFs and CMFs should be developed, although calibrated baseline HSM models remain appropriate for routine applications.

Ambros & Sedonik (Ambros & Sedoník, 2016) developed and evaluated transferable accident prediction models for network safety ranking in two Czech regions (South Moravian and Zlín), testing transferability across time and space. Separate models were developed to determine the feasibility of temporal and spatial transferability. Transferability tests indicated that models are not directly transferable between regions, but a combined model using data from both regions performed as well or better than individual regional models, suggesting that as more regional data are accumulated, a country-wide transferable model could be developed to support effective network safety ranking (Ambros & Sedoník, 2016).

Dadvar et al. (Dadvar, Lee, & Shin, 2020) proposed an improved local calibration method for the Highway Safety Manual (HSM) predictive approach to better estimate crash frequency at individual sites while maintaining aggregate accuracy. Unlike the standard HSM procedure, which uses a single local calibration factor, the method applies multiple calibration factors to SPF parameters and CMFs using weight and power functions, and showed that calibrating CMFs with additional parameters can substantially improve site-specific predictions, enhancing hotspot identification and safety interventions (Dadvar, Lee, & Shin, 2020). Additionally, it suggested developing locally estimated SPF models and adjusting the base conditions of HSM.

Al-Ahmadi et al. (Al-Ahmadi, et al., 2021) calibrated Highway Safety Manual (HSM) Safety Performance Functions (SPFs) for two multi-lane rural highways in Saudi Arabia (NHWY-80 and NHWY-85) using crash data from 2017–2019. According to the study, HSM SPFs frequently overestimated crashes, and calibration enhanced the accuracy of crash predictions, supporting better hotspot identification and road safety decision-making. Further research on the development of jurisdiction-specific SPFs for local conditions was recommended.

Srinivasan et al. (Srinivasan, Colety, Bahar, Crowther, & Farmen, 2016) examined the two key issues related to calibrating Highway Safety Manual (HSM) predictive models using crash data from rural two-lane roads in Arizona. Selecting an appropriate sample size for calibration should follow the statistical procedures proposed by Bahar and Hauer, rather than relying on recommendation from the HSM (Srinivasan, Colety, Bahar, Crowther, & Farmen, 2016). The study also highlighted the importance of using calibration functions when single calibration factors do not adequately represent local crash conditions.

La Torre et al. (La Torre, et al., 2019) developed two crash prediction models for estimating single-vehicle and multiple-vehicle fatal-and-injury crashes on Italian rural freeways for which Highway Safety Manual (HSM) methodology was adapted to European motorway conditions using jurisdiction-specific Safety Performance Functions (SPFs) and Crash Modification Factors (CMFs) derived from the PRACT project. To improve prediction accuracy, calibration factors were calculated to reflect the models with local crash frequencies.

Bhattarai, S. (Bhattarai, 2019) analyzed crash trends and site-specific geometric features at 17 major urban intersections in Kathmandu Valley. Using HSM techniques, the study assessed crash frequency at intersections, indicating that minor injuries occur more frequently than severe injuries. Intersections were ranked using crash frequency, crash rate, critical crash rate, and crash predictive techniques to determine high-priority areas for safety enhancements.

3. Methodology

The methodology began by identifying sites having four-lane undivided arterials, which were selected based on the availability of traffic volume data. Data were collected for each site, including historical crash records, traffic volumes, and roadway characteristics (such as segment length, presence of on-street parking, driveway density, fixed objects, etc). For both multiple-vehicle and single-vehicle collisions, jurisdiction-specific SPFs have been developed. The SPF estimates were adjusted using Crash Modification Factors (CMFs), and a local calibration factor was computed to refine the predictions.

Crash predictions were conducted using the Highway Safety Manual (HSM) predictive model for urban arterials. Data from fiscal years 2077/78 to 2079/80 were used for model calibration, while data from fiscal year 2080/81 were utilized for validation. Model performance was evaluated using statistical measures such as MAD and MAPE. To further assess model accuracy, a simple regression analysis was performed, and the R^2 value was determined. The methodological steps followed in this research are presented in Figure 2.

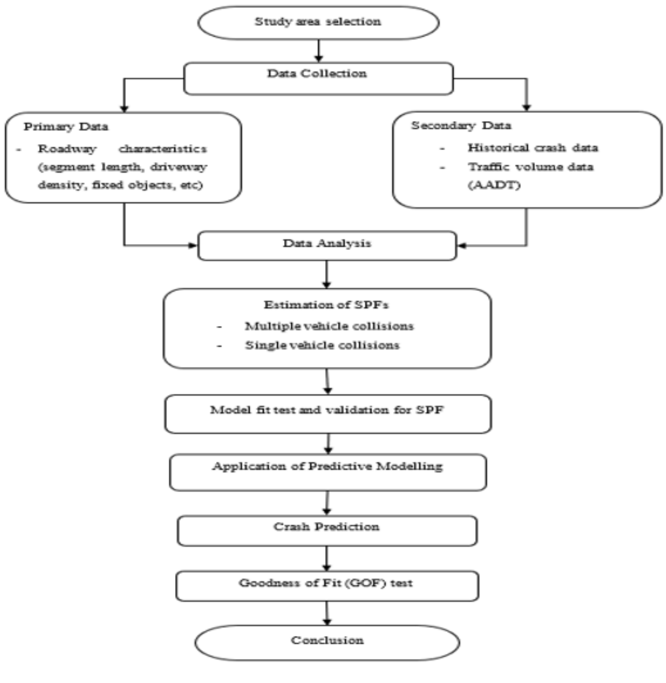

Figure 2: Methodological Flowchart

3.1 Study Area

The study was conducted in Kathmandu district. Seven sections with four-lane undivided urban arterials (Figure 3) were selected for evaluation due to their crucial role in mobility and the frequent crash occurrences, which are listed below:

Section 1: Chabahil-Mitrapark Segment

Section 2: Airport-Sinamangal Segment

Section 3: Sankhapark-Narayan Gopal Chowk Segment

Section 4: Basundhara-Narayan Gopal Chowk Segment

Section 5: Bansbari-Narayan Gopal Chowk Segment

Section 6: Maharajgunj-Narayan Gopal Chowk Segment

Section 7: Banasthali-Dhungedhara Segment

Figure 3: Study area Location

3.2 Data Collection

Traffic crash records from 2077/78 to 2080/81 were obtained from the Metropolitan Traffic Police Division, Singha Durbar for this study. Traffic volume data was obtained from official website of the Department of Roads (DoR). The offset distance and fixed object density were determined through on-site visits, while the segment length was obtained using Google Earth.

3.3 Data Analysis

The main steps for the analysis are as follows:

3.3.1 Data Compilation

The AADT for the roadway segment was collected from fiscal year 2077/78 to 2080/81. Detailed crash data for every year within this period was collected with the detailed information on types of crash, severity, location, and contributing factors. The data were systematically organized to ensure their completeness and accuracy, providing a reliable basis for subsequent analysis.

3.3.2 *Estimation of Safety Performance Functions*

This procedure involved developing jurisdiction-specific SPF for both multiple-vehicle and single-vehicle collisions. However, the crash records lacked sufficient detail to identify whether the crashes occurred on driveways. Consequently, only a few cases of driveway-related crashes could be identified. Due to a limited dataset, it was not possible to develop statistically valid models for driveway-related collisions. Therefore, driveway-related crashes were determined using HSM equation (refer (Equation *16*)). Hence, this study focuses primarily on prediction models for multiple-vehicle and single-vehicle crashes.

Multiple-Vehicle Non-driveway Collisions

Model I: $N_{brmv} = exp\ (a + b_1 \times ln(AADT) + b_2 \times ln(L))$ (Equation 4)

Model II: $N_{brmv} = exp\ (a + b_1 \times ln(AADT) + ln(L))$ (Equation 5)

Model III: $N_{brmv} = exp\ (a + b_1 \times ln(AADT) + b_2 \times L)$ (Equation 6)

The model includes AADT and segment length as independent variables. This study developed three different forms of the SPFs. The functional forms are identical to the HSM's SPFs. Log-transformed AADT is generally taken as a significant independent variable in HSM and previous research. Therefore, researchers investigate with alternative model forms and use log-transformation to reduce skewness in AADT data (Brimley, Saito, Schultz, & Reese, 2011). The Model I (Equation 4) is negative binomial regression model, which includes log-transformed AADT as explanatory variable and segment length as exposure variable. The Model II (Equation 5) is same model from HSM. The Model III (Equation 6) is NB regression model with log-transformed AADT as explanatory variable and segment length as independent variable.

Where,

a = an intercept

b_1, b_2 = regression coefficients for multiple-vehicle non-driveway collisions

N_{brmv} = Predicted average crash frequency of multiple-vehicle non-driveway collisions

L = Segment length

Single-Vehicle Crashes

The NCHRP report (Hardwood, et al., 2007) states that the single-vehicle crashes SPF is based on the multiple-vehicle collision SPF as statistically significant models for single-vehicle crashes were not found for all cases. The NCHRP research used a multiplicative factor to create a simple function for single-vehicle collisions, as no formal model is yet available. However, if only the multiplicative factor is considered, the AADT does not affect the dependent variable. Therefore, similar models from multiple-vehicle collisions were used to determine the coefficients of independent variables and an intercept, which are shown in (Equation *7*) (Equation *8*) and (Equation *9*).

Model I: $N_{brsv} = exp\ (a + b_1 \times ln(AADT) + b_2 \times ln(L))$ (Equation 7)

Model II: $N_{brsv} = exp\ (a + b_1 \times ln(AADT) + ln(L))$ (Equation 8)

Model III: $N_{brsv} = exp\ (a + b_1 \times ln(AADT) + b_2 \times L)$ (Equation 9)

Where,

a = an intercept

b_1, b_2 = regression coefficients for single-vehicle collisions

N_{brsv} = Predicted average crash frequency of single-vehicle non-driveway collisions

L = Segment length

3.3.3 Model Fit Test and Model validation

To verify the model fit analysis, a statistical model was crucial. Maximum likelihood estimation method has been employed widely in estimating Poisson, negative binomial and zero inflated regression models (Sharma & Landge, 2013). In this study, an information criterion test i.e. Akaike Information criteria (AIC), was used. This is due to the fact that the AIC statistic is correlated with the model log-likelihood (refer (Equation *10*)) and the models evaluated in this study are computed using maximum likelihood estimation (Kim, Anderson, & Gholston, 2015). Lower the AIC value, the better the model.

$$AIC = -2 \, Log \, L + 2K \quad \text{(Equation 10)}$$

Where, Log L is the log-likelihood of the model, and K is the number of estimated parameters.

The crash data from 2077/78 to 2079/80 were used for modelling, whereas the crash data from 2080/81 were used for validation. Model performance was evaluated using two statistical measures:

- Mean Prediction Bias (MPB)
- Mean Absolute Deviation (MAD)

Mean Prediction Bias (MPB)

The MPB assesses bias by comparing observed and predicted values in validation data (refer (Equation *11*)). Bias indicates the direction of error. Regression model that exhibit positive values are likely to overestimates crash frequency, and vice versa. Smaller absolute numbers imply a more accurate model for predicting crash frequency.

$$MPB = \frac{\Sigma(P_i - O_i)}{n} \quad \text{(Equation 11)}$$

Where,

P_i = Predicted value

O_i = Observed value

n = Sample size of validation data

Mean Absolute Deviation (MAD)

The discrepancy between observations and expected values is measured by the MAD (refer (Equation *12*)). Positive and negative prediction errors won't cancel each other out, which is how it varies from MPB. MAD can only be positive, in contrast to MPB. The average magnitude of prediction variability is measured by the MAD. It is preferable to have smaller values than larger ones (Washington, Persaud, Lyon, & Oh, 2005).

$$\boldsymbol{MAD = \frac{\Sigma|P_i - O_i|}{n}} \quad \text{(Equation 12)}$$

Where,

P_i = Predicted value

O_i = Observed value

n = Sample size of validation data

3.3.4 Application of Predictive Modeling Elements

- Crash Modification Factors (CMFs) were applied to modify the SPF estimates, taking into consideration specific roadway features such as on-street parking or the presence of medians.
- A local calibration factor was calculated and applied to refine the predictions, ensuring they accurately reflect the local traffic and roadway conditions.

3.3.5 Crash Prediction

Crash predictions for urban arterials were conducted using a predictive model based on the Highway Safety Manual (HSM) (AASTHO, 2009).

Predictive Models for Urban Arterial Roadway Segments is given by:

$$N_{predicted\ rs} = C_r \times (N_{br} + N_{pedr} + N_{biker}) \quad \text{(Equation 13)}$$

$$N_{br} = N_{spf\ rs} \times (CMF_{1r} \times CMF_{2r} \times CMF_{3r} \times CMF_{4r} \times CMF_{5r}) \quad \text{(Equation 14)}$$

Where,

$N_{predicted\ rs}$= predicted average crash frequency of an individual roadway segment for the selected year;

N_{br}= predicted average crash frequency of an individual roadway segment (excluding vehicle-pedestrian and vehicle-bicycle collisions);

$N_{spf\ rs}$= predicted total average crash frequency of an individual roadway segment for base conditions (excluding vehicle-pedestrian and vehicle-bicycle collisions);

The SPF component of N_{br}, designated as $N_{spf\ rs}$, is further divided into three components based on collision type which is shown in (Equation *15*).

$$N_{spf\ rs} = N_{brmv} + N_{brsv} + N_{brdwy} \quad \text{(Equation 15)}$$

Where,

N_{brmv}= predicted average crash frequency of multiple-vehicle non-driveway collisions for base conditions;

N_{brsv}= predicted average crash frequency of single-vehicle crashes for base conditions;

N_{brdwy}= predicted average crash frequency of multiple-vehicle driveway-related collisions.

Multiple Vehicle Driveway-Related Collisions

(Equation *16* determines the total number of multiple-vehicle driveway-related collisions within a roadway segment.

$$N_{brdwy} = \Sigma\, n_j \times N_j\, (AADT/15000)^t \quad \text{(Equation 16)}$$

Where,

N_j = Number of driveway-related collisions per driveway per year for driveway type j;

n_j = number of driveways within the roadway segment of driveway type j, including all driveways on both sides of the road;

t = coefficient for traffic volume adjustment (shown in Table 1)

Table 1: Regression coefficient for AADT (t) for all driveways

Road Type	2U	3T	4U	4D	5T
t	1	1	1.172	1.106	1.172

Vehicle-Pedestrian Collisions

(Equation 17 estimates the number of vehicle-pedestrian collisions per year for a roadway segment.

$$N_{pedr} = N_{br} \times f_{pedr} \quad \text{(Equation 17)}$$

$$f_{pedr} = \frac{K_{ped}}{K_{non}} \quad \text{(Equation 18)}$$

Where,

N_{pedr}= predicted average crash frequency of vehicle-pedestrian collisions for an individual roadway segment;

f_{pedr}= pedestrian crash adjustment factor;

K_{ped}= observed vehicle-pedestrian crash frequency;

K_{non}= observed frequency for all crashes not including vehicle-pedestrian and vehicle-bicycle crashes.

Vehicle-Bicycle Collisions

(Equation *19* estimates the number of vehicle-bicycle collisions per year for a roadway segment.

$$N_{biker} = N_{br} \times f_{biker} \quad \text{(Equation 19)}$$

$$f_{biker} = \frac{K_{bike}}{K_{non}} \quad \text{(Equation 20)}$$

Where,

N_{biker}= predicted average crash frequency of vehicle-bicycle collisions for an individual roadway segment;

f_{biker}= bicycle crash adjustment factor;

K_{bike}= observed vehicle-bicycle crash frequency;

K_{non}= observed frequency for all crashes not including vehicle-pedestrian and vehicle-bicycle crashes.

Crash Modification Factors for Roadway Segments

The CMFs used in (Equation *14*), to modify the SPF for urban arterial roadway segments, to reflect deviations between the model's base conditions and the local site conditions, are presented below;

CMF$_{1r}$ - On-Street Parking

The absence of on-street parking on a roadway segment is taken as base condition.

CMF$_{2r}$ - Roadside Fixed Objects

The CMF for roadside fixed object, where present, is determined using (Equation *21*).

$$CMF_{2r} = f_{offset} \times D_{fo} \times p_{fo} + (1.0 - p_{fo}) \quad \text{(Equation 21)}$$

Where,

CMF_{2r}= Crash Modification Factors for the effect of roadside fixed objects on total crashes;

f_{offset} = fixed-object offset factor from Table 2;

D_{fo} = fixed-object density (fixed objects/mi) for both sides of the road combined;

p_{fo} = fixed-object collisions as a proportion of total crashes;

Table 2: Fixed-Object Offset Factor

Offset to fixed objects (O_{fo}) (ft)	2	5	10	15	20	25	30
Fixed-object offset factor (f_{offset})	0.232	0.133	0.087	0.068	0.057	0.049	0.044

The value of f_{offset} for 30-ft was used when the average offset to fixed objects exceeds 30-ft.

CMF$_{3r}$ - Median Width

For undivided facilities, the value of this CMF is taken as 1.

CMF_{4r} – Lighting

The AMF for lighted roadway segments is determined using (Equation *22*).

$$CMF_{4r} = 1.0 - (p_{nr} \times (1.0 - 0.72 \times p_{inr} - 0.83 \times p_{pnr})) \quad \text{(Equation 22)}$$

Where,

CMF_{4r}= Crash Modification Factors for the effect of roadway segment lighting on total crashes;

p_{inr} = proportion of total night-time crashes for unlighted roadway segments that involve a fatality or injury;

p_{pnr} = proportion of total night-time crashes for unlighted roadway segments that involve property damage only;

p_{nr} = proportion of total crashes for unlighted roadway segments that occur at night.

The traffic records do not disclose information on whether the road segments were lighted or not during night-time crashes. Due to the lack of this information, the values of the proportions (i.e., p_{inr}, p_{pnr}, and p_{nr}) are taken from the table provided by HSM which is shown in Table 3.

Table 3: Night-time Crash Proportions for Unlighted Roadway Segments

Roadway Segment type	Fatal and Injury (p_{inr})	PDO (p_{pnr})	Proportion of crashes that occur at night (p_{nr})
4U	0.517	0.483	0.365

CMF_{5r} - Automated Speed Enforcement

The absence of automated speed enforcement is taken as base condition.

Calibration Factor

The calibration factor can be computed as:

$$C_r = \frac{\Sigma\ Observed\ Crashes}{\Sigma\ Predicted\ Crashes\ (unadjusted)} \quad \text{(Equation 23)}$$

Where,

C_r= calibration factor for roadway segments of a specific type developed for use in a particular geographical area

The HSM's SPF has been generated from the base conditions present in the roads of the states whose data were utilized to develop the HSM's crash prediction model. Table 4 shows the base conditions for the urban arterial roadway segments. The alteration of local conditions from base conditions is adjusted through Crash Modification Factors (CMFs), which are discussed above.

Table 4: HSM's Base Conditions for Urban Roadway Segments

Parameters	Base Condition
Road type (2U, 3T, 4U, 4D, 5T)	-
Length of segment, L (mi)	-
AADT (veh/day)	-
Type of on-street parking (none/parallel/angle)	none
Lighting	not present
Auto speed enforcement	not present
Roadside fixed object density (fixed objects/mi)	not present

Parameters	Base Condition
Offset to roadside fixed objects (ft)	not present
Calibration Factor, C_r	1

4. Results and Discussion

4.1 Estimation of Safety Performance Functions

Negative binomial regression models were used to develop the Safety Performance Functions (SPFs) of four-lane undivided (4U) arterials for multiple-vehicle collisions and single-vehicle collisions. Using Python's statistical libraries, the intercept and regression coefficients of the SPF models were estimated from three years of crash data (fiscal years 2077/78 to 2079/80) collected from different locations. The estimated parameters (intercept and regression coefficients) for multiple-vehicle collisions and single-vehicle collisions are presented in

Table 5 and

Table 6, respectively.

Table 5: Estimated parameters for SPFs of multiple-vehicle collisions

Road Type	Model	Intercept (a)	b1 (log_AADT)	b2 (log_L or L)
4U	Model I	-15.178	1.673	-0.403
	Model II	-12.661	1.568	
	Model III	-13.786	1.63	-1.311

Table 6: Estimated parameters for SPFs of single-vehicle collisions

Road Type	Model	Intercept (a)	b1 (log_AADT)	b2 (log_L or L)
4U	Model I	3.646	-0.303	-0.629
	Model II	4.847	-0.278	
	Model III	5.494	-0.345	-1.949

For multiple-vehicle collisions (

Table 5), the coefficient of the log-transformed AADT (b_1) is positive (ranging between 1.568 and 1.673), implying that higher crash frequencies are consequences of increased traffic volume. The impact of segment length varies across the models because it was included in different forms, either as a log-transformed variable, an offset, or a linear term, which results in different magnitudes and interpretations of the b_2 coefficient.

In contrast, the log-transformed AADT coefficients for single-vehicle crashes (

Table 6) are negative in all models (range from -0.278 to -0.345), indicating reduction in this type of crashes with increasing traffic volume. The coefficient of segment length (b_2) varies with the model specification. The segment length has a negative impact on crash frequency in models where it is explicitly included (i.e., Model I and III).

These results show that multiple-vehicle collisions are highly susceptible to traffic exposure, but single-vehicle collisions are significantly impacted by characteristics of roadway length and remain persistent even at reduced volumes.

4.2 Result of the Fit Test and Validation of SPFs

The outcomes of the model fit test for SPFs of multiple-vehicle collisions, as well as single-vehicle collisions, are shown in Table 7 and Table 8, respectively.

In comparing AIC values of Model I, Model II, and Model III, Model III is more accurate than other two for multiple-vehicle collisions, due to the lowest value. Additionally, MPB and MAD values (Table 9) of Model III were closer to zero than other models.

For single-vehicle collisions, the MPB and MAD values (Table 10) across all the models were nearly identical, which indicates that all the models perform similarly. In this context, Model III is regarded as the most suitable and accurate model for predicting single-vehicle collisions, as only AIC value is the decisive factor.

The results of the model validation test for multiple-vehicle collision and single-vehicle collision are shown in Table 9 and Table 10, respectively.

Table 7: Model fit test for SPFs of multiple-vehicle collision

Road Type	**Model**	**AIC**	**Log-Likelihood**
4U	Model I	224.670	-109.335
	Model II	227.692	-111.846
	Model III	222.133	-108.067

Table 8: Model fit test for SPFs of single-vehicle collision

Road Type	**Model**	**AIC**	**Log-Likelihood**
4U	Model I	73.222	-33.611
	Model II	86.972	-41.486
	Model III	72.311	-33.156

Table 9: Results for Model Validation for Multiple-Vehicle Collision

Place	Observed	Model I			Model II			Model III		
		Predicted	MPB	MAD	Predicted	MPB	MAD	Predicted	MPB	MAD
Chabahil	20	30.145	7.159	13.844	23.198	11.811	19.980	31.415	7.082	13.414
Sinamangal	33	35.809			42.782			36.089		
Banasthali	17	40.320			18.997			41.017		
Basundhara	61	37.602			32.409			38.839		
Bansbari	20	20.753			31.581			20.534		
Sankhapark	16	42.549			67.069			40.644		
Maharajgunj	13	22.932			46.639			21.040		

Table 10: Result for Model Validation for Single-Vehicle Collision

Place	Observed	Model I			Model II			Model III		
		Predicted	MPB	MAD	Predicted	MPB	MAD	Predicted	MPB	MAD
Chabahil	1	3.015	1.556	1.556	1.948	1.582	1.582	3.173	1.554	1.554
Sinamangal	2	2.323			2.569			2.358		

Place	Observed	Model I			Model II			Model III		
		Predicted	MPB	MAD	Predicted	MPB	MAD	Predicted	MPB	MAD
Banasthali	0	3.639			1.348			3.664		
Basundhara	1	2.715			2.046			2.837		
Bansbari	2	2.307			3.237			2.274		
Sankhapark	1	1.945			3.034			1.841		
Maharajgunj	0	1.948			3.892			1.732		

4.3 Calculation of Calibration Factor (C_r)

The observed and predicted crashes for selected locations were determined using crash data from fiscal year 2077/78 to 2079/80, whose summary is presented in Table 11. Based on these values, the calibration factor was subsequently calculated.

Table 11: Summary of Observed and Predicted Crashes

Location	Observed crashes	Predicted crashes
Chabahil	39	135.44
Airport	43	69.4
Sankhapark	42	42.21
Basundhara	72	105.14
Bansbari	28	44.05
Maharajgunj	19	52.62
Banasthali	27	62.55
Total	**270**	**511.41**

The calibration factor (C_r) is computed as in Equation **Error! Reference source not found.**).

$$C_r = \frac{\Sigma \text{ Observed Crashes}}{\Sigma \text{ Predicted Crashes (unadjusted)}}$$

$$= \frac{270}{511.41}$$

$$= 0.53$$

Using the calibration factor (C_r), the frequency of crashes was predicted for the year 2080/81, and the results are presented in Table 12.

4.4 Goodness of Fit (GOF) measures

Goodness-of-fit measures include the percentage error (PE) (refer Equation 24), the mean absolute deviation (MAD) (refer Equation 25) and the mean absolute percentage error (MAPE) (refer Equation 26). The lesser value of these measures suggests higher model fit.

$$Percentage\ error\ (PE)\ = \frac{|Observed\ crashes - Predicted\ crashes|}{Observed\ crashes} \times 100\% \qquad \text{Equation 24}$$

$$\text{Mean Absolute Deviation (MAD)} = \frac{\Sigma|Observed\ crashes - Predicted\ crashes|}{n} \qquad \textit{Equation 25}$$

$$\textit{Mean Absolute Percentage Error (MAPE)} = \left(\frac{\Sigma|Obs\ crashes - Pred\ crashes|}{Observed\ crashes}\right)/n \times 100\% \qquad \textit{Equation 26}$$

Table 12: Result of Goodness of Fit (GOF) test

Location	Observed	Predicted	lObs-Predl	Percentage error	MAD	MAPE
Chabahil	26	20	6	23.73		
Airport	39	44	5	11.98		
Sankhapark	23	28	5	21.24		
Basundhara	73	45	28	38.86	8.608	24.586
Bansbari	24	16	8	33.75		
Maharajgunj	17	14	3	15.03		
Banasthali	20	26	6	27.51		
Total	**222**	**192**	**60**	**172**		

Due to the underlying randomness and annual variations in crash occurrences, certain places have relatively high percentage errors. Although crashes may increase throughout the model training period, they may reduce significantly in the testing year, resulting in discrepancies between observed and predicted values. Since crash frequencies do not increase or decrease uniformly throughout the years, such fluctuations lead to higher prediction errors.

A simple regression analysis was conducted, and the R^2 value was determined as illustrated in Figure 4. It yields the R^2 value of 0.6513, which is relevant for the regression performed. The result shows that the calibration factor test has an acceptable value.

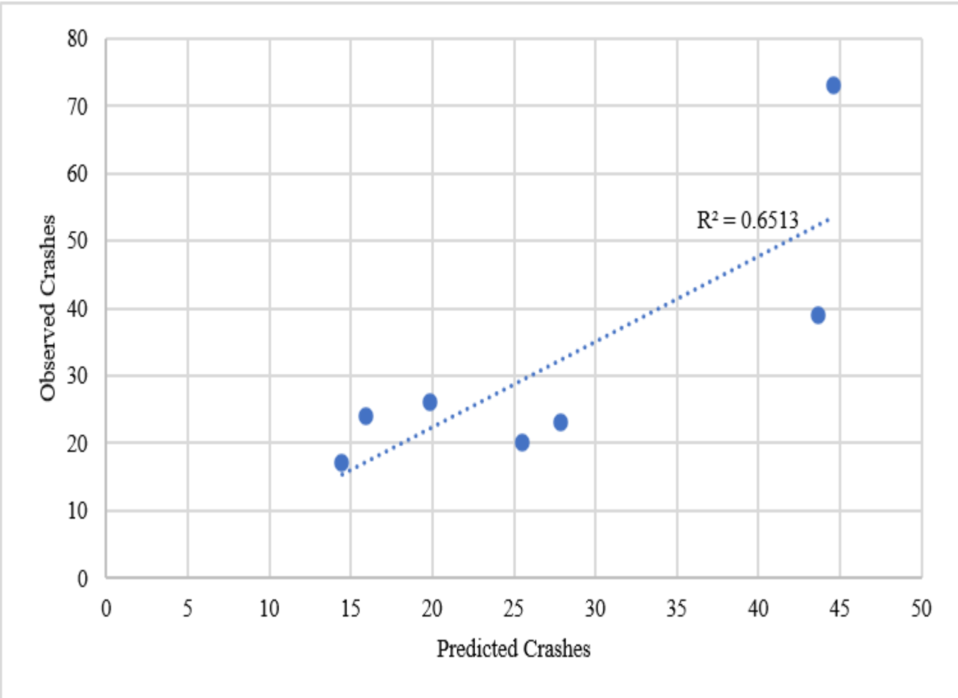

Figure 4: Regression analysis for four-lane undivided arterials

5. Conclusions and Recommendations

5.1 Conclusions

This study developed and validated local SPFs to evaluate the effectiveness of HSM prediction models for four-lane undivided arterials in Kathmandu district. Three SPF models for single-vehicle and multiple-vehicle collisions were formulated using crash data from fiscal years 2077/78 to 2079/80. With the lowest AIC value and appropriate MPB and MAD values, Model III offered the best statistical fit.

Based on observed and predicted crash frequencies, a calibration factor of 0.53 was obtained. This value indicates that the uncalibrated HSM model significantly overpredicts crashes on arterial roads in Kathmandu, which is due to the variation in the USA and Nepal road environment, such as roadside conditions, traffic composition, and underreporting of crashes, especially minor crashes. After applying the calibration factor, crash data from fiscal year 2080/81 were used to validate its applicability. The obtained R^2 value of 0.6513 and reasonable MAD and MAPE values indicate a reasonable degree of model accuracy.

In order to conduct accurate safety assessments and implement targeted interventions, this research emphasizes the significance of creating locally calibrated crash prediction models. The findings are helpful for policymakers and transportation planners who want to employ data-driven approaches to increase road safety on Kathmandu's arterial network.

5.2 Recommendations

Based on the findings of this study, the following recommendations are proposed:

- As this study utilizes crash data from the Metropolitan Traffic Police Division, which may be underreported, particularly for minor crashes. This may result in fewer observed crashes and affect the calibration factor. Future research should therefore consider an integrated crash reporting system, linking traffic police, hospitals, and insurance.
- Future studies can integrate GIS-based crash mapping at the network level to identify high-risk roadway segments throughout the study area.
- SPFs should be developed for other classifications of roads for evaluating safety in Kathmandu.
- Future models can incorporate variables other than traffic volume and segment length.

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