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EXPLORING THE VIABILITY OF SURROGATE SAFETY MEASURES BASED ON SMARTPHONE DATA FOR THE SAFETY ASSESSMENT AND SCREENING OF URBAN ROAD STREET SEGMENTS

Hamid MARWI[1], Mehdi FALLAH-TAFTI[2], Mojtaba RAJABI-BAHAABADI[3]
[1, 2, 3] Department of Civil Engineering, Yazd University, Yazd, Iran

***Abstract**:*
The focus of traffic safety research has recently shifted from reactive to proactive safety management approaches. In reactive approaches, historical crash data is used to identify accident-prone locations or black spots. However, this approach is inherently reactive, focusing on accidents that have already occurred, requiring several years of accident data. Recently, surrogate safety measures have been adopted as a proactive alternative for identifying black spots. Nowadays, the widespread use of smartphones equipped with GPS systems makes it possible to utilize mobile GPS data to identify accident-prone locations. In this study, GPS-derived surrogate safety measures extracted from smartphone data are used to predict the frequency of potential accident incidences on road segments. On this basis, several Poisson-based statistical models and Artificial Neural Network (ANN) models were developed based on the data collected by smartphones on two carriageways of a long arterial street in Mashhad, Iran. GPS trajectory data, including vehicle speed, acceleration, and location, were collected using a GPS data recorder application installed on the smartphones of drivers and passengers traveling along the carriageway. The results indicated that both the Poisson-based and ANN models can predict crash frequency with reasonable accuracy. However, the ANN model, comprising surrogate speed and acceleration-related safety measures, demonstrated slightly better performance than Poisson-based regression models. The models were then successfully tested for their ability to identify accident-prone segments. Our findings indicated that data obtained from smartphones can be used as surrogate measures for assessing road safety and ranking accident-prone segments along urban roads.

Keywords: *Black Spots, Surrogate Road Safety Measures, Accident Prediction Models, Smartphone Data*

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Contact:
1) hamidmarwi7@gmail.com [https://orcid.org/0009-0005-9937-7901]; 2) fallah.tafti@yazd.ac.ir [https://orcid.org/0000-0001-6844-3316] – corresponding author; 3) mojtaba.rajabi@yazd.ac.ir [https://orcid.org/0000-0002-1392-5729]

1. Introduction

The proliferation of motorized transportation has offered numerous benefits; however, it has also given rise to significant societal challenges, including traffic congestion, air pollution, and traffic accidents (Lowe, 2007). Road traffic crashes result in fatalities and severe injuries, imposing a substantial burden on society and families. According to a report published by the World Health Organization (WHO), there were over 1.19 million fatalities worldwide resulting from road traffic accidents in 2021. As of 2019, road crashes remained the leading cause of death among children and young people aged 5 to 29 years and the 12th leading cause of death across all age groups (WHO, 2023). This underscores the urgent need for innovative approaches to reduce accidents and to identify accident-prone locations proactively.

Conventional methods for road safety assessment and identifying accident-prone locations rely heavily on historical crash data for safety analysis (Xu et al., 2024). However, these methods suffer from several limitations. First, as crashes are rare events, a long period of time is required to collect sufficient data for reliably estimating road safety levels (Nikolaou, Ziakopoulos, et al., 2023). Second, underreporting biases might occur as some property-damage-only (PDO) crashes are not recorded in official reports (Khadka et al., 2022). Third, and most importantly, crash-based methods are inherently reactive, meaning safety interventions are implemented only after crashes occur rather than proactively preventing them (Khanal & Edelmann, 2023). Finally, while multiple factors influence crash risk—such as driver psychophysical condition, visibility, road surface condition, road lighting condition, environmental condition and vehicle technical state—these factors are often difficult to measure directly. Speed and acceleration serve as integrated behavioral outcomes of these underlying causes, providing a practical, scalable, and theoretically sound approach for data-driven safety analysis using smartphone data. To overcome these limitations, developing accurate and reliable methods to identify accident-prone locations proactively is crucial for evaluating road safety. By adopting proactive approaches, it is also possible to enhance road safety by identifying the underlying causes of accidents and resolving their issues before actual accidents occur.

To date, various efforts have been made to employ surrogate measures for the proactive identification of accident-prone locations and the assessment of road safety levels (Ambros et al., 2024; Lee & Rouphail, 2024; Nadimi et al., 2025; Nikolaou, Dragomanovits, et al., 2023; Wang et al., 2021). Surrogate safety measures are indicators, parameters, or quantities used as a proactive approach to evaluate road safety by identifying hazardous conditions before crashes occur. They serve as alternative or complementary methods to conventional crash-based analysis, allowing for the assessment of safety levels without relying on historical accident data (Nikolaou, Ziakopoulos, et al., 2023).

Recent advancements in intelligent technologies have brought significant opportunities for employing surrogate measures to determine accident-prone segments. Accordingly, in this study, GPS data extracted from smartphones is utilized to predict the frequency of traffic accidents at various road segments and to identify accident-prone segments. The main contributions of this study are as follows:

- This study investigates the potential of smartphone-collected data for evaluating road safety in urban areas.
- This study introduces several surrogate safety measures based on GPS data. We use these measures as independent variables and develop two regression-based models and one neural network-based model to predict crash frequency at the segment level as a function of these surrogate safety measures.
- The study also explores which of the defined surrogate measures are most effective for predicting crash frequency and identifying accident-prone segments.

The remaining parts of this paper are structured as follows. Section 2 provides a review of previous studies. Section 3 describes the study area and data collection procedure. Section 4 briefly describes the statistical and neural network models developed to predict crash frequency. Section 5 presents the results of the statistical and neural network models and provides a discussion on the results. Finally, Section 6 concludes the paper and offers suggestions for future research.

2. Literature review

Network screening involves systematically assessing road networks to identify segments with a high risk of crashes. The identified segments, known as blackspots, will then be investigated further to determine their safety issues. A common approach for identifying blackspots is estimating crash frequency using regression techniques that incorporate historical crash data along with factors related to traffic exposure, road geometry, and environmental conditions (Stipancic et al., 2019). However, in cases where accident data are scarce or unavailable, surrogate safety measures and real-time crash prediction techniques can be used.

Surrogate safety measures (SSM) aim to assess road safety without relying on accident data by using traffic and road characteristics as indirect safety assessment indicators. Real-time prediction of collision risks, based on surrogate safety indicators, allows for the identification of potential accident hotspots. By quantifying collision risks on different parts of a road network, traffic managers can proactively monitor and manage the safety of that network. Wang et al. (2021). Surrogate safety measures are divided into three categories: 1) time-based SSM, 2) deceleration-based SSM, and 3) energy-based SSM. Time-based SSM evaluates the risk of an interaction based on how close it is in time to a potential collision. The most widely used time-based SSM is Time-to-Collision (TTC), first introduced by Hayward (1971). TTC is defined as the time remaining until a crash occurs between two vehicles, assuming that both the trajectory and speed difference remain unchanged. Several additional time-based safety measures have been developed based on the TTC, including time headway (Vogel, 2003), modified time-to-collision (Ozbay et al., 2008), and time to collision with the disturbance (Xie et al., 2019). Deceleration-based measures are a class of safety indicators that evaluate how a vehicle's deceleration can prevent a crash. These measures consider additional parameters compared to time-based SSMs, such as the reaction time of the following vehicle, maximum braking rate, emergency braking rate, road friction coefficient, and gravitational acceleration (Wang et al., 2025). Some of the most common deceleration-based surrogate safety measures include the crash potential index (Cunto, 2008), proportion of stopping distance index (Astarita et al., 2012), and time exposed rear-end crash risk index (Rahman et al., 2018). Finally, energy-based SSMs were developed to measure the severity of an interaction. DeltaV (Shelby, 2011), conflict severity index (Bagdadi, 2013) and conflict index (Alhajyaseen, 2015) are some well-known energy-based surrogate safety measures.

2.1. Previous research based on SSM extracted from smartphone data

GPS-enabled smartphones can record vehicle speed, acceleration, and location data, which can then be shared on a server for analysis to identify accident-prone areas and unsafe driving behaviors. With advancements in smartphone technology, their role in this area has become more prominent, as these devices can estimate vehicle speeds with an error of less than 3 km/h and determine location with an error of less than 5 meters (Zhao et al., 2017). Moreover, in the realm of Intelligent Transportation Systems (ITS), the use of vehicle tracking has expanded. With the advancements in smartphone technology and new smart technologies incorporated into vehicles, obtaining vehicle-based data has become more convenient. Utilizing vehicles as probe data collectors enables large-scale traffic data collection in a cost-effective manner.

Several studies have employed data extracted from smartphones to analyse road safety. For example, Ahmadinejad et al. (2017) examined the possibility of using the number of negative accelerations as a surrogate measure to evaluate road safety. They observed a significant correlation between crash frequency and the number of negative accelerations. Strauss et al. (2017) utilized deceleration rates extracted from a smartphone application to explore the correlation between reported cyclist road injuries and deceleration rates. Employing Spearman's rank correlation coefficient, they compared the rankings of sites based on the expected number of injuries and the deceleration rates. They found that the ranks of expected injuries and dangerous decelerations correlated at 0.60 for signalized intersections, 0.53 for non-signalized intersections, and 0.57 for roadway segments. Stipancic et al. (2018) used smartphone data to investigate the behavioral characteristics of drivers, particularly accelerating and braking maneuvers. They found that crash frequency at the link and intersection levels is positively correlated with both maneuvers. Similarly, Stipancic et al. (2021) examined the relationship between traffic flow surrogate safety measures and crash frequency in three Canadian cities. The study showed that braking, congestion, and speed variation are positively associated with crash frequency, while mean speed is negatively associated. Ziakopoulos et al. (2022) employed driving data from smartphone sensors and digital map data for urban road networks in Athens, Greece. The study used several spatial models to predict harsh braking event frequency. The modeling revealed that harsh braking frequencies are positively correlated with segment length and adjusted vehicle pass count for each segment, negatively correlated with gradient and neighborhood complexity. Deliali et al. (2023) developed a model for predicting highway accidents using smartphone data. They explored the relationship between crash frequency and three unsafe events, namely, harsh acceleration, harsh braking, and speeding. Their findings revealed a positive correlation between harsh acceleration events and crash frequency. Liu et al. (2023) developed a machine learning-based model considering hard braking as a surrogate safety measure. They observed a strong correlation between high deceleration events and crash frequency. Ziakopoulos (2024) examined factors influencing harsh braking and harsh acceleration events using real-world telematics data from smartphones, as well as traffic data and road geometry data. The study identified that higher traffic occupancy, traffic speed, segment length, and gradient values increase the probability of harsh braking occurrences. Additionally, higher speed differences, traffic occupancy, segment length, and vehicle pass count for each segment were recognized as contributing factors to harsh acceleration. Nikolaou et al. (2025) employed spatial analysis to assess harsh braking events in a region with sparse crash data. They applied advanced statistical and machine learning models using smartphone-derived driving behavior data. Their findings demonstrated that the spatial zero-inflated negative binomial model surpassed non-spatial alternatives in performance.

These studies confirm that acceleration- and speed-based surrogate measures are widely accepted and reliable indicators in proactive safety assessment. Moreover, real-time kinematic data from individual vehicles can be used to identify accident-prone locations as a complementary approach to conventional methods. Using the deviation of speed and acceleration as independent variables in an accident prediction model is a powerful, pragmatic, and theoretically sound approach. It bypasses the immense practical difficulties of measuring direct causal factors such as road user behavior, visibility, driver psychomotor condition, vehicle technical condition, etc., and instead, focuses on their unified, measurable consequence—the vehicle's motion. This allows for the proactive, scalable, and objective assessment of traffic safety risk, transforming the field from reactive crash analysis to proactive risk management. Smartphone-derived data, in particular, offers a promising resource for this purpose. The present study extends the literature by introducing several surrogate safety measures based on GPS data that can be extracted from smartphones.

This study utilized kinematic data from individual vehicles on each road segment. The data included two speed-based surrogate measures—the 50th and 90th percentile speeds—and six acceleration-based measures: the 10th and 50th percentile deceleration rates, the 50th and 90th percentile acceleration rates, and the 50th and 90th percentile absolute acceleration rates. This range of measures was selected to identify the most relevant predictors during model development. Subsequently, the proposed measures are employed as input variables in statistical and neural network models to estimate crash frequency. Finally, the significant variables are identified from the proposed measures. This research contributes to the field by employing a comprehensive set of derived speed and acceleration metrics, applying them to both conventional and AI-based neural network models, an approach that represents a novel combination.

3. Methodology

3.1. Description of the study area and data collection Procedure

To achieve the primary objective of this research, it was necessary to select an appropriate route for the study. The selected route must have a history of significant traffic accidents and feature diverse road geometries, surrounding land uses, and traffic management conditions. For this purpose, one of the major arterial streets located in the city of Mashhad, a large city with over 3.5 million population located in the northeast of Iran, was selected. The selected street is a 24-meter-wide dual-carriageway street with an 11-meter-wide carriageway in each direction functioning as a primary distributor arterial street and called North Tabarsi Boulevard, with a length of 4.7 kilometers, as depicted in Fig. 1. It is worth mentioning that the speed limit for this street is 60 kilometers per hour, and the peak flow rate is approximately 5000 vehicles/hour per carriageway.

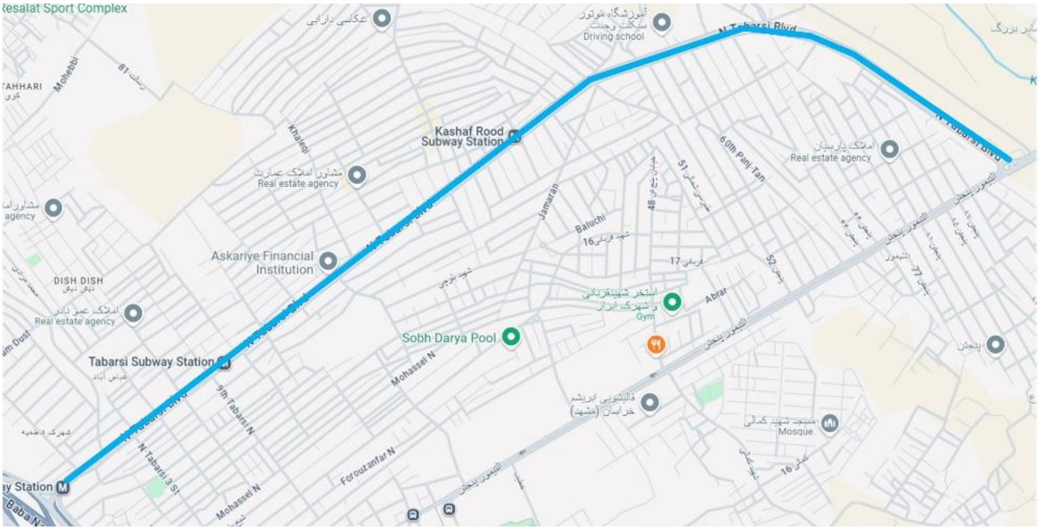

Fig. 1. Study Area: North Tabari Boulevard, Mashhad, Iran (Source: maps.google.com)

GPS trajectory data, including vehicle speed, acceleration, and location, were collected using the Bump Recorder app (*https://www.bumprecorder.com*), installed on the smartphones of drivers and passengers traveling along the carriageway. Participating drivers were informed beforehand that their data would be used solely for research purposes and were encouraged to follow their routine driving behavior. Overall, the methodology outlined in reference (Darawade et al., 2016) was followed in this research. To validate the reliability of the Bump Recorder data, concurrent recordings were obtained using a commercial GPS vehicle tracker (TELTONIKA FM920). The average speed difference between the smartphone data and GPS data collected by the commercial GPS vehicle tracker was calculated for 76 segments on the northbound carriageway and found to be 1.58 meters per second. Similarly, for 83 segments on the southbound carriageway, the average speed difference was 1.2 meters per second. These results confirmed the expected accuracy of smartphone data. Furthermore, four-year accident data for this street from 2018 to 2022 was obtained from the Mashhad Municipality. Each carriageway was divided into 100-meter segments, and unique identifiers were assigned to facilitate data entry and model development.

Let us assume that each carriageway is divided into *n* segments. Based on the data extracted from smartphones, the speed and acceleration of each vehicle at multiple points along each segment were calculated. Let $\boldsymbol{P}_j = \{p_1, p_2, \ldots, p_m\}$ denotes the set of points along segment j for which the speed and acceleration of each vehicle were calculated. Let us assume that $\boldsymbol{V}_{ij} = \left\{V_{ij}^{p} | p \in \boldsymbol{P}_j\right\}$ and $\boldsymbol{A}_{ij} = \left\{A_{ij}^{p} | p \in \boldsymbol{P}_j\right\}$ represent the sets of calculated average speeds and accelerations for vehicle i traversing segment j, respectively. Let $Q_{ij}^{V}(k)$ denote the k-th percentile of the data in data set of $\boldsymbol{V}_{ij}$. Based on these assumptions, we define two speed-based surrogate measures for segment j as follows:

$$V_{50} = \text{Median}\left(\left\{Q_{ij}^{V}(50) | i = 1,2, \ldots, I\right\}\right), \tag{1}$$

$$V_{90} = \text{Median}\left(\left\{Q_{ij}^{V}(90) | i = 1,2, \ldots, I\right\}\right), \tag{2}$$

where I represent the number of vehicles that participated in the survey and traversed the segment and Median(.) is a function that calculates the median of a set of numbers. It should be noted that V_{50} serves as a measure of the average speed, whereas V_{90} corresponds to the speed of high-speed vehicles.

Furthermore, let assume that $Q_{ij}^{|A|}(k)$ denote the k-th percentile of the absolute values of acceleration rates in the $\boldsymbol{A}_{ij}$data set. Similarly, let assume that $Q_{ij}^{A+}(k)$

and $Q_{ij}^{A-}(k)$represent the k-th percentile of positive and negative acceleration rates in $\boldsymbol{A}_{ij}$ data set, respectively. Accordingly, six acceleration-based surrogate measures are defined as follows:

$$A_{10}^{-} = \text{Median}\left(\{Q_{ij}^{A-}(10)|i = 1,2, \dots, I\}\right), \quad (3)$$

$$A_{50}^{-} = \text{Median}\left(\{Q_{ij}^{A-}(50)|i = 1,2, \dots, I\}\right), \quad (4)$$

$$A_{50}^{+} = \text{Median}\left(\{Q_{ij}^{A+}(50)|i = 1,2, \dots, I\}\right), \quad (5)$$

$$A_{90}^{+} = \text{Median}\left(\{Q_{ij}^{A+}(90)|i = 1,2, \dots, I\}\right), \quad (6)$$

$$A_{50} = \text{Median}\left(\left\{Q_{ij}^{|A|}(50)|i = 1,2, \dots, I\right\}\right), \quad (7)$$

$$A_{90} = \text{Median}\left(\left\{Q_{ij}^{|A|}(90)|i = 1,2, \dots, I\right\}\right), \quad (8)$$

For the development of crash prediction models, the average annual number of accidents occurring on a road segment (denoted as y) is considered as the dependent variable. Additionally, the eight variables defined in the above equations are used as independent variables. A summary of statistics of the variables used in this paper is provided in Table 1.

Table 1. Descriptive statistics of variables used in crash prediction models

Variables	Mean	S.D	Min	Max
y	4.704	1.777	2	13
V_{90}	10.933	2.325	6.473	15.063
V_{50}	9.965	2.536	5.371	14.749
A_{10}^{-}	-0.581	0.261	-1.243	-0.146
A_{50}^{-}	-0.279	0.118	-0.709	-0.082
A_{90}^{+}	0.698	0.195	0.316	1.152
A_{50}^{+}	0.323	0.083	0.158	0.590
A_{90}	0.58	0.188	0.247	1.368
A_{50}	0.314	0.1050	0.01	0.671

3.2. Model Development

In this paper, two types of models are employed for predicting crash frequency. The first type is regression-based models, and the second type is artificial neural network models. A brief overview of these models is provided later in this section. For model development, the dataset described in Section 3 was randomly partitioned into training (80%) and testing (20%) subsets. The training subset was used for model calibration, while the testing subset was reserved to evaluate the predictive performance of the models.

3.2.1. Regression-based models

Several statistical regression models—namely Poisson, negative binomial, zero-inflated negative binomial, and zero-inflated Poisson—were initially developed to model crash frequency using STATA/MP.17 software. These models were estimated to assess whether overdispersion or an excess number of zero counts existed in the dataset. Since the negative binomial and zero-inflated models are generalizations of the Poisson model, they are only required when significant overdispersion or structural zeros are detected. Based on model diagnostics and statistical tests, no substantial overdispersion or excess zeros were observed; therefore, there was no compelling need to use these generalized models. Consequently, the Poisson regression model was selected as the most parsimonious and statistically appropriate approach for this study.

Crash frequency represents count data consisting of non-negative integer values, making the Poisson distribution a natural choice for modeling such outcomes. Unlike the normal distribution, which is continuous and defined over the real line, the Poisson distribution is discrete and assigns probability exclusively to non-negative integers. The probability mass function of a Poisson-distributed count variable Y_j with mean λ_j is given by:

$$P\left(\left(Y_j = y_j|\lambda_j\right)\right) = \frac{exp(-\lambda_j)\lambda_j{}^{y_j}}{y_j!} \quad (9)$$

To relate crash counts to explanatory variables, the Poisson model is formulated within the generalized linear modeling (GLM) framework using a log-link function:

$$log(\lambda_j) = \beta_0 + \beta_1 X_{j1} + \beta_2 X_{j2} + \dots + \beta_T X_{jT} \quad (10)$$

or equivalently:

$$\lambda_j = exp(\beta_0 + \beta_1 X_{j1} + \beta_2 X_{j2} + \dots + \beta_T X_{jT}) \quad (11)$$

where λ_j represents the expected number of crashes for segment j, $X_{j1}, X_{j2,}\dots$and X_{jP} are the values of independent variables for segment j and $\beta_1, \beta_{2,}\dots$, and β_P are coefficients for the independent variables and β_0 is the intercept.

3.2.2. Artificial neural network-based model

Artificial neural networks (ANNs) represent a class of machine learning models inspired by the structure and functioning of the human brain. Among them, the multilayer perceptron (MLP) is one of the most widely used feedforward neural networks, owing to its computational efficiency, conceptual simplicity, and ability to generalize effectively even when trained on relatively small datasets (Übeyli, 2007). An MLP consists of an input layer, one or more hidden layers, and an output layer (Choong et al., 2020). Each neuron in the input layer corresponds to an independent variable of the dataset. The hidden layers serve as intermediate computational stages that receive inputs from the preceding layer, perform a weighted summation of these inputs, and apply a nonlinear activation function to generate the outputs that are subsequently passed to the next layer. The output layer produces the final predictions of the network. Mathematically, the output of a neuron j in either a hidden or output layer is defined as:

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$$y_j = f\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right) \tag{12}$$

where x_i denotes the input from neuron i of the previous layer, w_{ij} represents the weight of the connection between neuron i and j, b_j is the bias term, and f is the activation function, which may take the form of a sigmoid, hyperbolic tangent or rectified linear unit function. In the present study, the hyperbolic tangent function was selected as the activation function due to its ability to center outputs around zero, facilitating faster convergence.

The network is trained using the backpropagation algorithm, which iteratively updates the connection weights and biases to minimize the discrepancy between the predicted outputs and the observed values. This discrepancy is quantified using the Roote Mean Squared Error (RMSE) function as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\sum_{j=1}^{m}\left(y_j^k - \hat{y}_j^k\right)^2} \tag{12}$$

where N is the number of training samples, m is the number of output neurons, y_j^k is the actual value of the j-th output for the k-th sample, and $\hat{y}_j^k$ is the corresponding network prediction.

4. Results

In this study, two Poisson regression models and one neural network-based model were developed to predict crash frequency as a function of the surrogate measures defined in Section 3.

The first Poisson regression model (Model 1) incorporates a constant term, while the second model excludes it. It should be noted that we employed the well-known stepwise method for selecting independent variables of the regression models. The stepwise method systematically identifies the subset of independent variables that best explain variation in the dependent variable. It determines the most significant independent variables by iteratively adding or removing independent variables based on a statistical criterion such as p-value. The results of the first model is presented in Table 2. As indicated in Table 2, the Poisson regression model with a constant term comprises two independent variables A_{90}^{+} and A_{10}^{-}, along with an intercept. Both variables are significant at the 95% confidence level (p-values < 0.05). The model's log-likelihood is -165. The Wald chi-square test statistic is 36.47, with a p-value of less than 0.05, indicating that the overall model is statistically significant.

Table 2. Results of the Poisson regression model with a constant term

Variable	Coefficient	Std. err.[a]	*p*-value	95% CI[b]	
A_{10}^{-}	-0.522	0.183	0.004	-0.88	-0.163
A_{90}^{+}	1.185	0.224	0	0.746	1.625
Constant	0.518	0.178	0.004	0.168	0.868

[a]Std. err. = Standard Error, [b] CI = Confidence Interval.

The second Poisson regression model (Model 2) excludes the constant term. The results in Table 3 show that this model includes three independent variables: A_{10}^{-} , A_{50}^{-}, and A_{90}^{+}. The log-likelihood of this model is -168.2. Similar to the first model, the Wald test results indicate that the overall model is also statistically significant at the 95% confidence level. This means that at least one of the predictors has a significant effect on the dependent variable.

Table 3. Results of the Poisson regression model without a constant term

Variable	Coefficient	Std. err.[a]	*p*-value	95% CI[b]	
A_{10}^{-}	-0.497	0.238	0.037	-0.964	-0.03
A_{90}^{+}	1.62	0.153	0	1.32	1.92
A_{50}^{-}	-0.819	0.45	0.069	-1.702	0.063

[a]Std. err. = Standard Error, [b] CI = Confidence Interval.

A multilayer perceptron (MLP) neural network model (Model 3) was also developed to predict crash frequency. In this model, the input layer represents the independent variables influencing crash frequency, while the output layer corresponds to the four-year average accident count per road segment. The hidden layer acts as an intermediary between the input and output layers, facilitating network training. For activation functions, we selected the hyperbolic tangent for the hidden layers (a common choice for nonlinear modeling) and the identity function for the output layer. We trained multiple configurations with varying independent variables and selected the model with the lowest RMSE on the testing set as the best model. This metric quantifies the average deviation between model predictions and empirical observations, with lower values indicating higher predictive accuracy. The architecture of the best-performing model, selected for having the lowest Root Mean Square Error (RMSE) on the testing set, is illustrated in Fig. 2. This model comprises one hidden layer with three neurons, and the input variables are A_{90}^{+}, A_{10}^{-}, A_{50}^{+}, V_{50} and A_{90}.

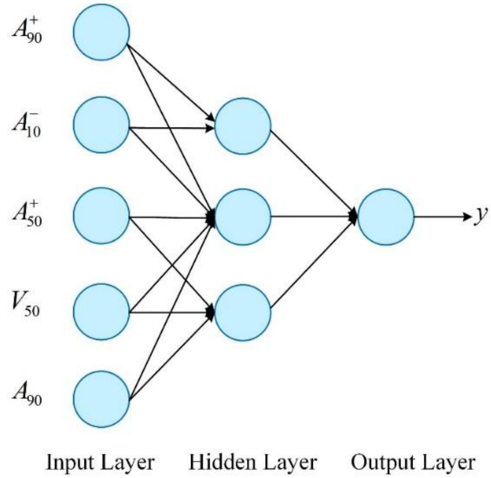


Fig. 2. Architecture of the Best-Performing ANN Model

A sensitivity analysis was performed on the independent variables of the best ANN model utilizing IBM SPSS Statistics 27 to identify the most significant variables affecting crash frequency prediction. Fig. 3 illustrates the relative importance of each variable, which is derived from perturbations observed in the model's predictions. Consistent with findings from the regression models, variables A_{90}^{+} and A_{10}^{-} exhibit the strongest influence on the ANN's performance, underscoring their key role in crash frequency prediction as surrogate safety measures.

To evaluate predictive accuracy, the RMSE was calculated for each model on a testing dataset. The RMSE values are presented in Fig. 4. The neural network-based model (Model 3) achieved the lowest RMSE, followed by the Poisson regression model with a constant term (Model 1). Fig. 5 shows scatterplots of predicted versus observed values for all three models. The slopes of the fitted regression lines are close to 1, and the R^2 value for the neural network model is higher than those of the regression-based models.
Finally, the models were applied to identify accident-prone "black spot" segments using a criterion of 12 or more accidents within a three-year period. Fig. 6 compares the ability of each model to correctly identify these segments, showing that Model 1 and Model 3 are superior to Model 2.

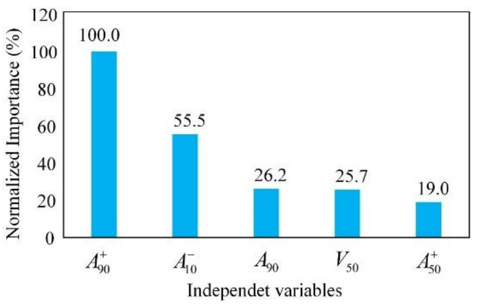


Fig. 3. Normalized importance (%) of input variables in the ANN model

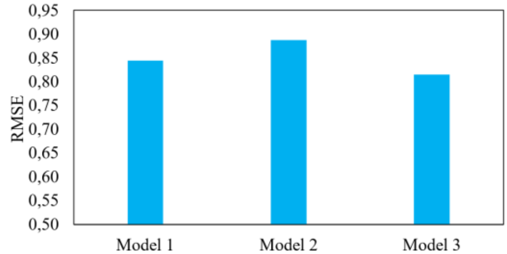
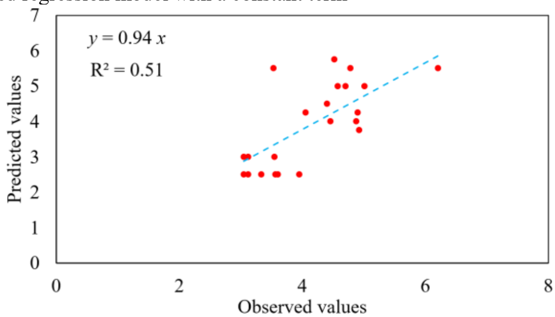
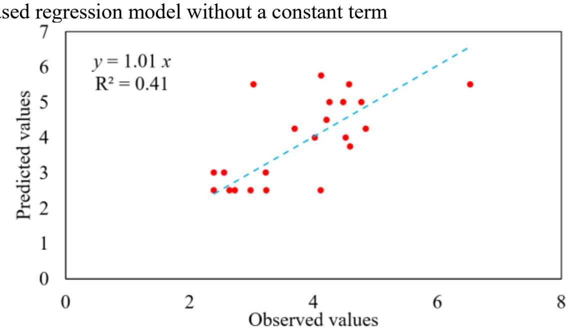


Fig. 4. RMSE values for the three models tested: Poisson regression with intercept (Model 1), Poisson regression without intercept (Model 2), and ANN model (Model 3)

a) Model 1: the Poisson-based regression model with a constant term



b) Model 2: the Poisson-based regression model without a constant term



c) Model 3: the ANN-based model

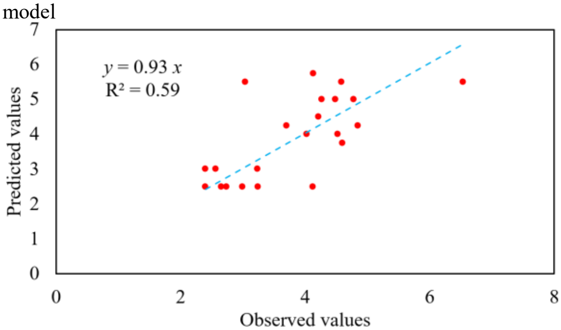


Fig. 5. Scatter plot of observed crash frequency against predictions

5. Discussion

The results of two Poisson regression models and one neural network-based model, developed to predict crash frequency as a function of the speed-derived and acceleration-derived surrogate safety measures, are presented in this section.

The regression model results indicate that speed-derived variables were not statistically significant predictors in the final models. In contrast, variables derived from negative acceleration (e.g., A_{10}^{-}) and positive acceleration (e.g., A_{90}^{+}) were found to significantly influence crash frequency. This suggests that kinematic events related to sudden deceleration (e.g., abrupt braking) and rapid acceleration (e.g., aggressive driving or overtaking maneuvers) are more directly associated with crash risk. The signs of the coefficients in the regression models are intuitive and align with theoretical expectations. The positive sign for A_{90}^{+} indicates that an increase in high-percentile positive acceleration is associated with a higher number of crashes. Furthermore, the negative signs for A_{50}^{-} and A_{10}^{-} are also logical; since these variables represent negative values (deceleration), an increase in their absolute magnitude corresponds to more intense braking events and, consequently, a greater crash risk.

The superior performance of the neural network model (Model 3), as evidenced by its lower RMSE and higher R^2 value (Fig. 4 and Fig. 5), suggests that the relationship between surrogate measures and crash frequency may be complex and non-linear. The ANN's ability to capture these intricate patterns allows it to provide slightly more accurate predictions than the generalized linear models. The sensitivity analysis of the ANN model (Fig. 3) reinforces the findings from the regression models, underscoring the key role of A_{90}^{+} and A_{10}^{-}- as the most influential surrogate safety measures. This consistency across different modeling paradigms, strengthens the conclusion that these acceleration-based metrics are robust indicators of crash frequency. This finding is consistent with previous research, which suggested that variables related to acceleration and deceleration are better indicators of harsh driving maneuvers and potential accident risk than variables based on speed (e.g., Ahmadinejad et al., 2017; Strauss et al., 2017; Stipancic et al., 2018; Stipancic et al., 2021; Ziakopoulos et al., 2022; Deliali et al., 2023; Liu et al., 2023; Ziakopoulos, 2024; and Nikolaou et al., 2025). Our findings complement previous work, suggesting that identifying robust surrogate safety measures depends on testing and validating a broader set of variables derived from acceleration/deceleration and speed of vehicles.

One potential application of the developed accident prediction models, based on surrogate safety measures, would be to rank different street segments in accordance with their predicted accident frequencies. A criterion used in the UK to identify black spots was used to present the possibility of applying the developed models for this purpose. Based on this criterion, a location is considered as a black spot if at least 12 accidents have occurred there within a three-year period (Shafabakhsh & Sajed, 2022). Using this criterion, we identified accident-prone segments using observed data and predictions obtained by the models. Fig. 6 compares the ability of each model to identify blackspot segments correctly. As shown in Fig. 6, accident-prone segments in over 90% of cases can be correctly identified using predictions of the models. It is also evident that Model 1 and Model 3 are superior to Model 2 for identifying accident-prone segments. The finding that Model 1 and Model 3 can correctly identify accident-prone segments in over 90% of cases highlights their potential as effective tools for network screening and prioritizing safety interventions. The inferior performance of Model 2 (without a constant term) suggests that the model specification with an intercept provides a more reliable basis for this critical task.

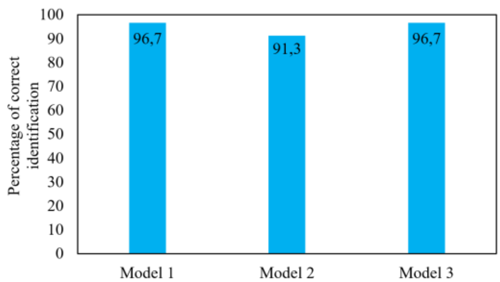


Fig. 6. Percentage of correctly identified blackspots by each model: Model 1 (Poisson with intercept), Model 2 (Poisson without intercept), and Model 3 (ANN)

6. Conclusion

Crash risk is influenced by multiple factors including driver behaviour, vehicle and road environment conditions, which are often difficult to measure directly. In contrast, speed and acceleration data, along with their deviations, can serve as effective surrogate safety measures. These metrics represent the measurable outcomes of underlying causal factors and can be derived directly from vehicle dynamics using in-vehicle sensors like smartphones or dedicated trackers. Thus, the primary objective of this research was to investigate the feasibility of utilizing smartphone-derived data as surrogate safety measures for evaluating road safety. To accomplish this, speed, acceleration, and positional data from vehicles traversing a dual-carriageway road were collected using the Bumprecoder application. Subsequently, two Poisson-based statistical regression models and a multilayer perceptron (MLP) ANN-based model were developed and evaluated. In these models, a broad set of variables derived from acceleration and speed data of vehicles was used and tested.

Model performance was evaluated using two complementary criteria, 1) RMSE and 2) the percentage of correctly identified black spots, to capture both predictive accuracy and practical usefulness. Based on these two evaluation criteria, among the statistical models, the Poisson-based regression model with an intercept term demonstrated superior performance. As for the ANN-based model, the architecture incorporating five input variables yielded the best predictive accuracy. As a practical application, the models were tested for their ability to identify accident-prone road segments. The results of the study showed that the models can be used to identify accident-prone segments.

To extend this research, further researches are still required to ensure that such surrogate safety measures could resemble underlying causes of accident risks in other situations and different sections of road networks. Moreover, future studies could compare the performance of real-time data from vehicle trackers and smartphones in ranking hazardous road segments. Additionally, the possibility of using real-time data to integrate a risk assessment feature into navigation apps such as Google Maps could be explored. Such a feature could categorize accident risk into low, medium, and high levels, providing alerts to drivers in high-risk areas.

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