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Traffic safety and the rural road environment: Assessing the impact of combined roadway conditions on crash incidence

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This study was designed to explore the combinational effect of the roadway and traffic characteristics of national rural roads on fatal and serious-injury crashes in Namibia. Namibia, like many other countries in Southern Africa, experiences high numbers of high-severity crashes, particularly on its rural road network. The study applied Generalised Poisson regression models to analyse the study dataset. The results indicate that high-severity crashes are almost always influenced by a combination of factors, not simply the presence of a single factor. For example, on higher-order roads, a higher proportion of heavy vehicles in the traffic stream had the highest absolute impact on high-severity crash levels, but this effect was heightened when hilliness, wider lanes, surfaced shoulders and higher operating speeds were also present at the same time. On lower-order roads a higher proportion of light vehicles in the traffic stream had the highest absolute impact on high-severity crashes, and again this was compounded in the presence of wider unpaved shoulder widths and higher operating speeds. Overall, wider lane widths and wider unpaved shoulder widths, especially when found in combination with each other, were linked to a subsequent increase in higher-severity crash levels on higher-order roads. The study shows conclusively that the development of safer roads relies not on simply implementing minimum safety standards for individual design elements, but on understanding the relationship between features of road design, traffic parameters and road safety, to recognise which coincidences of factors affect crash risks on different classes of road. This knowledge can result in more careful road design so that crash likelihood is reduced.

INTRODUCTION

The demand for more transport and mobility, which has surged in recent years, has precipitated an increase in the levels of motorisation in the modern world (Starkey *et al* 2017). One of the major issues arising from and being attributed to high levels of motorisation is road traffic crashes, which are recognised now to be one of the leading causes of premature mortality globally. The World Health Organisation (WHO) reports that about two-thirds of premature deaths caused by injuries stem from road traffic crashes (WHO 2018), and that on average around 1.3 million people are killed in traffic crashes every year.

Road traffic crashes are complex events that are difficult to predict due to the fact that their constituent causes generally include a combination of several interrelated factors including the geometric design of the road, vehicle and environmental factors, and driver behaviour and perceptions (Fitzpatrick 2014; Turner *et al* 2015; Ambunda & Sinclair 2019; Chatterjee & Mitra 2019).

Notwithstanding the general recognition that road-user behaviour on the roadways is the primary cause of road traffic crashes, the road environment and its properties (geometric, pavement and traffic characteristics) play a significant role in influencing crash risk, due to their impact on how a driver perceives and responds to the roadway (Taylor *et al* 2000; Deller 2013; Ambunda & Sinclair 2019).

Roadway components are designed around minimum design standards which in turn are based on consideration of expected driver characteristics, reactions and

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traffic conditions (Bester & Makunje 1998). Examples include average driver height (for vertical crest standards), average reaction time (to determine intersection sight distances) and numerous others. Driver behaviour, however, is seldom predictably based on simple characteristics or averages. Most often a driver responds to a road environment based on the messages that he or she 'reads' from the roadway conditions (Bester & Makunje 1998; Ambunda & Sinclair 2019). These may include – but are not limited to – components of road geometry, road surface and traffic characteristics relating to traffic composition and speed (Fitzpatrick 2014; Ambunda & Sinclair 2019; Chatterjee & Mitra 2019). The response of drivers to individual elements is shaped by a number of things, including (among others) their age and driving experience, the cognitive load placed on them at the time, their stimulus-response compatibility (largely determined by previous exposure to the particular road element); and their prior expectations (Vaa 2014; Bongiorno *et al* 2017). How individuals respond to a complex road environment is really only partially understood. Some studies (for example, looking at driver behaviour in curves, or in the presence of wide shoulders) have started to build a better understanding of how individual elements of the road environment may influence driver behaviour, but this knowledge is only partial and is particularly inadequate when two or more characteristics exist in parallel (Deller 2013; Ambunda & Sinclair 2019). In analysing crash locations where high-severity crashes have been experienced repeatedly, it becomes possible to investigate how the combination of roadway conditions at the time of the crash may have influenced crash risk, based on the coincidence of factors in each location.

Most developing countries, including Namibia, are faced with a lack of locally derived or locally tested tools to predict and mitigate crash likelihood. The context-sensitivity of even the most common road safety standards has seldom been evaluated in countries of the developing world, where road user behaviour and training (in particular) may differ from what is expected in other parts of the world. Furthermore, the costs associated with achieving or maintaining international safety standards can be extremely high. As such, road safety authorities in countries such as Namibia tend to be reactive instead of proactive to road safety issues. For this reason it becomes particularly important to capacitate transport engineers to detect and even predict high-risk road and traffic characteristics that have the potential to influence the frequency and severity of road crashes, by using information that is readily available, dependable and cost-effective.

Reducing the frequency and severity of road traffic crashes continues to be a priority for transportation and traffic engineers. The UN Decade(s) of Action for Road Safety (2010–2030) has highlighted the need for road designers and authorities to better understand the complexity of crash cause and injury severity, and to work more proactively to reduce the potential for high-severity crashes. The UN has defined a number of road safety performance targets that countries across the world, including Namibia, have signed up to achieve (Ambunda 2018). These include better road management strategies, which in turn include improved systems to understand road crash causation.

Road safety analyses can be useful in identifying national road sections prone to high road crash incidences and high injury severity, while determining the factors significantly contributing to the high road crash occurrences (Noland & Oh 2004). Estimating the factors influencing road crashes on a given national rural road is important in evaluating the different road design variable covariates and alternatives (Wang *et al* 2013; Glavić *et al* 2016), as well as to understand which factors may be more challenging to drivers than are conventionally assumed. Various methods have been used to carry out road safety analysis, with several statistical methods commonly used by road traffic engineers (Hauer 2014; Murthy & Rao 2015; Ihueze & Onwurah 2018). These methods have, however, tended to approach crash risk from the perspective of single or limited numbers of covariates (Ben-Bassat & Shinar 2011; Liu *et al* 2016; Gitelman *et al* 2019).

To this end, the goal of the study was to develop a method to quantitatively investigate the extent of the combined effect of various national rural road geometric, pavement and traffic covariables on crash occurrences for Namibia's rural roads, providing a straightforward, mathematically sound way of predicting road crashes based on combinations of these covariates. The intention was to develop a method that could be used by traffic engineers in similar operating conditions to predict crash likelihood where there may not be perfect crash data, but where roadway and traffic data is accessible.

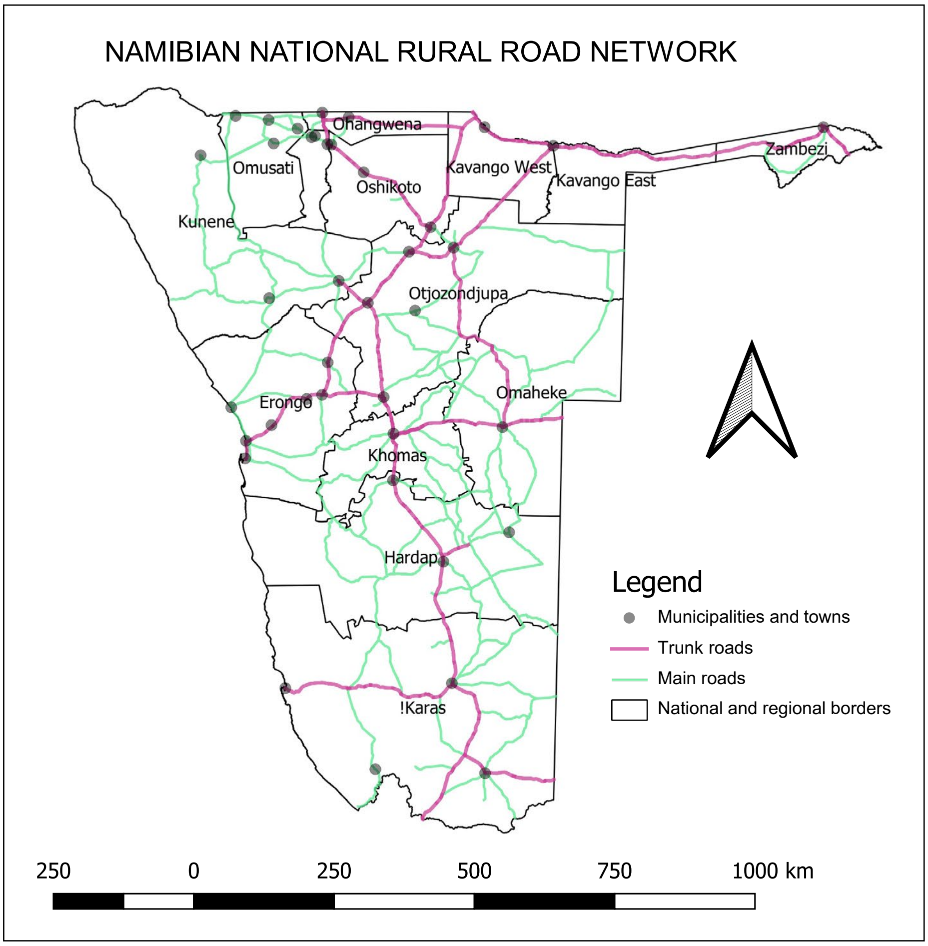

Figure 1 Namibian national rural road network

Table 1 Functional classes of rural and urban roads TRH26 (CSRA 1988)

Main class	Acronym	Rural classes
High-order rural roads (HORR)	R1	Rural principal arterial
	R2	Rural major arterial
	R3	Rural minor arterial
Low-order rural roads (LORR)	R4	Rural collector road
	R5	Rural local road
	R6	Rural walkway

DATA

Study area

Fatal- and serious-injury crash data was sourced for the Namibian national rural road network from the Namibian National Road Safety Council (NRSC), the Motor Vehicle Accident Fund of Namibia (MVA) and the Namibian police for the aforementioned road classes (see Figure 1 on page 39). The national road network was divided into several classes (see Table 1) according to the functions of the roads and the traffic volumes experienced on these roads using the Technical Recommendations for Highways on Road Classifications and Access Management (TRH 26) (CSRA 1988). The national rural road network spans all fourteen regions in Namibia and is maintained by the Namibian Roads Authority through subsidies provided by the Namibian Government, road user taxes and other fees collected by the Road Fund Administration (RFA) (Eggleston *et al* 2016).

Data on roadway design and conditions was obtained from the Roads Authority (RA) of Namibia. This focused on traffic volumes, speeds (operational, design and posted), road lane characteristics, road shoulder characteristics, road alignment, sight distances, access density, and pavement conditions. The collection of roadway data also involved on-site data collection on selected rural roads to supplement or corroborate data obtained from the relevant authorities. A summary of the covariates used in the model development procedure is presented in Table 2. Sixteen covariates were included in the model development process, of which 14 were tested in the models. The covariates were divided into two groups, namely numerical and categorical covariates. Of these covariates, nine related to the geometric characteristics of the rural roadway system and seven related to the characteristics of the rural roadway, describing the traffic modal split, terrain and roadway surface types and conditions.

Crash data

The study focused on higher-severity crashes (fatal- and serious-injury crashes) on trunk and main roads on the national rural road network. Crash data was obtained from the three main authorities responsible for crash reporting in Namibia (NRSC, MVA and the Namibian police). Using the crash data, the crash rates were determined as crashes per million vehicle kilometres per kilometre of road section over the study period of five years (2012–2016) (see Figure 2). The study analysis required continuous, reliable and accurate historical crash data, with information on traffic characteristics, traffic exposure covariates and the road environment, all of which are vital for an appropriate statistical analysis. The historical crash data collected from the Namibian road safety authorities was not geo-coded (this is a common problem in crash reporting in many developing countries), with the majority of the site-specific crash information missing. As a result, it was necessary for the study to address the deficiencies in both the crash and roadway data by developing an approach to remove incomplete crash record data and gather additional

Table 2 Descriptive statistics of crash model covariates

Descriptive statistic summary of covariates						
	Covariate	Minimum	Maximum	Mean	Standard deviation	Variance
Numerical	AADT_Light (AADTL)	85	14005	2328.44	2921.117	8532926.924
	AADT_Heavy (AADTH)	2	1400	345.29	376.970	142106.055
	AADT_Total	91	15362	2673.73	3231.762	10444282.947
	Operating_Speed (Ops)	0	120	44.02	53.010	2810.020
	Lane_Width (LW)	2.940	12.450	5.156	2.552	6.513
	No_Lanes (NL)	1	6	1.79	.683	0.466
	Surface_SW (SSW)	0.000	3.175	0.255	0.562	0.316
	Ground_SW (GSW)	0.000	8.9900	1.713	0.652	0.425
	Horizontal_(Curves/Length) (Hor)	0.000	0.709	0.176	0.143	0.020
	Access_Density (AD)	0.000	0.409	0.121	0.086	0.007
	Section_Length (SL)	12.230	22.967	15.462	1.486	2.207
	SSD	15	2215	179.76	63.002	3969.274
Categorical	Surface_type (ST)	0	1	–	–	–
	Shoulder_type (ShoT)	0	1	–	–	–
	Terrain_Vertical (TV)	0	1	–	–	–
	Pavement_Condition (PC)	0	1	–	–	–

site-specific information to enable a comprehensive statistical analysis of crash locations on national rural roads.

METHOD

Model development

The study developed Generalised Linear Models (GLMs) to predict national rural road crash incidences and investigate the combinational effects of geometric and traffic characteristics on road safety. The approach involved the aggregation of design and traffic factors, and fatal and serious injury (FSI) to satisfy the mathematical form assumptions of the prediction models – namely (i) to generate logical results that do not cause the prediction of negative crash incidences and should ensure a prediction of zero crashes for zero values of exposure and length variables, and (ii) there must exist a known link function that can linearise the model form for the purpose of coefficient estimation (Ghanbari 2017). The modelling approach was tested and validated using data from two datasets, representing FSI crashes on higher- and lower-order rural roads. Through the use of data manipulation it was possible to satisfy the assumptions of the GLMs and thus develop robust crash prediction models (CPMs). The study produced and compared the GLM CPMs using the Generalised Poisson (GP) models and Negative Binomial models to determine the best-performing model.

The GLMs that were developed share a number of unique properties, such as linearity and a common method for parameter estimation that allow the development of effective CPMs for highways. The GLMs consist of the following three components (Oppong 2012):

1. A random component, which specifies the conditional distribution of the response variable Y_i given the exploratory variables x_{ij}
2. A linear function of the regression variables, called the linear predictor, on which the expected value μ_i of Y_i depends:

$$Y_i = \alpha + \beta_1 X_{i1} + \ldots + \beta_k X_{i1} = x'_i\beta \quad (1)$$

3. An invertible link function:

$$g(\mu_i) = \eta_i \quad (2)$$

The invertible link function transforms the expectation of the response to the linear predictor. The inverse of the link function is sometimes called the mean function:

$$g^{-1}(\eta_i) = \mu_i \quad (3)$$

The GLMs are an extension of the linear models to include response variables that follow any probability distribution in the exponential family of distributions (Eenink *et al* 2005; Field 2013; Denis 2021). Several measures were used to examine the validity of the models and how they fit the data in the study. These measures, given in Section 4.5, include the Scaled Deviance (SD), Pearson's Chi-Square (PCS), Akaike Information Criterion (AIC), Corrected Akaike Information Criterion (AICc) and Bayes Information Criterion (BIC).

Outlier analysis

The study applied two-dimensional (2D) box plots as a diagnostic tool for detecting outliers and data-influential points, and ultimately used the winsorisation technique to address detected outliers in the dataset (see Figure 2). Winsorising is the process of

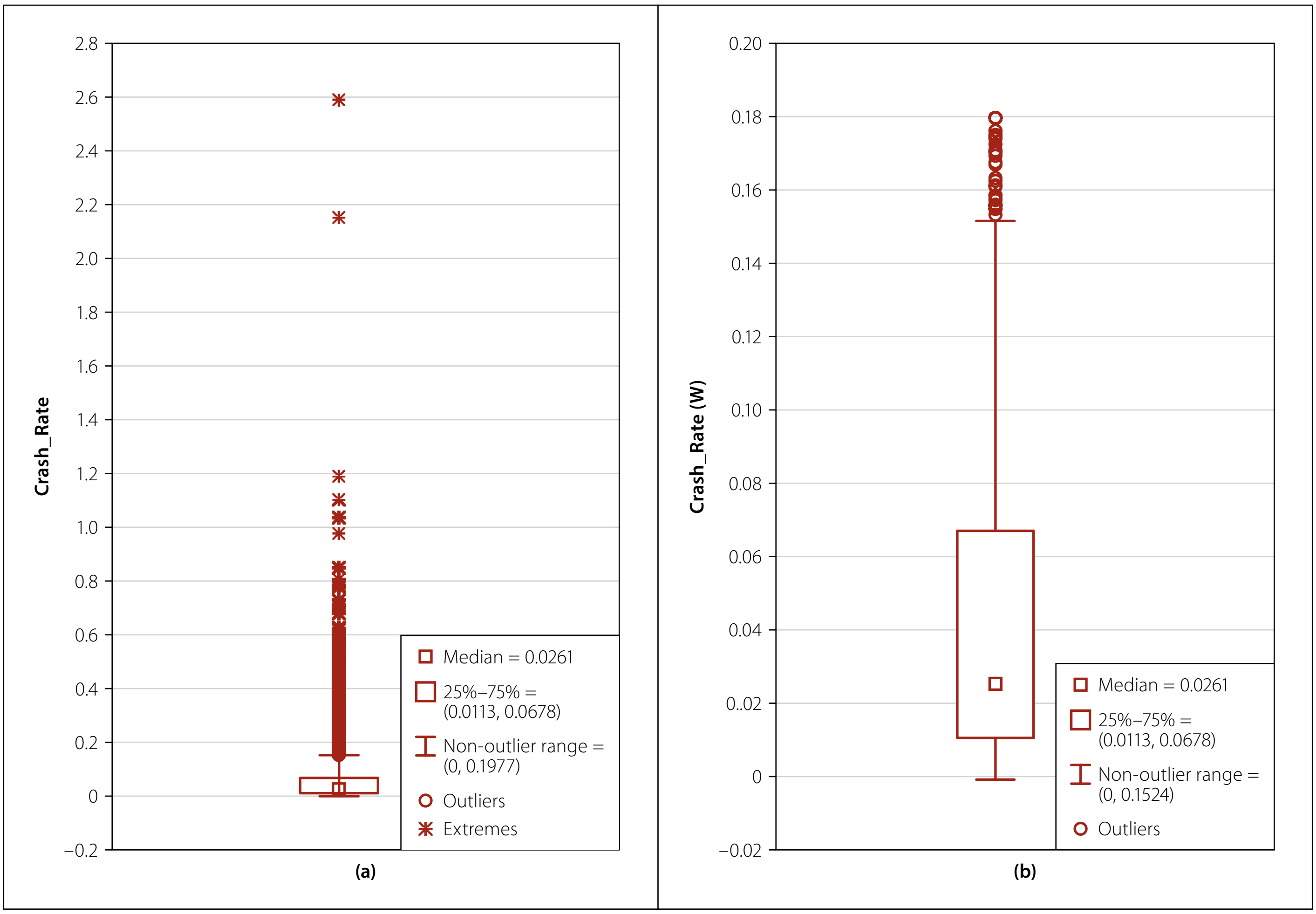

Figure 2 2D box plots of crash rate distribution before and after winsorisation

replacing a specified set of extreme values of a given variable in a set of sample data with specified values computed from the data (Chambers 2000; Reifman & Keyton 2010). The outliers were not removed from the dataset, even though they were extreme data points not typical of the rest of the crash data used in the study. The study recognised that the presence of these data points could have a significant impact on the estimates of the safety performance parameters of the models, thus a more robust outlier detecting and inclusion method was adopted in the study for outlier resistance modelling to allow for robust safety inferences by down-weighting (winsorising) the outlying crash observations rather than rejecting them. The winsorised models provide a superior fit and standard deviations for the parameter estimates.

A predefined rule was used to adjust an outlying (positive) value Y_i of the dataset variable Y downwards, leaving the remaining values unchanged (Hicks & Fetter 1991; Reifman & Keyton 2010). The value of the adjusted variable is denoted Y_i^* and the corresponding winsorised estimator adjusted to a fixed cut-off is represented by Equation 4.

$$\hat{Y}_t = \sum_{j=1}^{n} adj\ w_j^t y_j \tag{4}$$

Where:

t = truncation level

y_j = reported crash rate for the j^{th} unit

$$adj = \frac{\sum_n w_j}{\sum_n w_j^t}$$

$$w_j^t = w_j,\ \text{if } w_j y_j \le t\ \frac{t}{y_j},\ \text{if } w_j y_j > t$$

The weights of the observations of which the expanded weighted value was larger than t (where t = 0.75) were truncated so that the expanded values were equal to t. The t value was determined after observing the distribution of the data points and where the extreme data points were positioned. The truncated portions were then smoothed over for all observations.

Crash model biplots

Biplots are a graphical representation of information in an $n \times p$ data matrix, with information in rows representing samples and information in columns representing covariates. In the principal component (PC) analysis, plots were obtained by graphing the first two principal components of the units (Gower *et al* 2011). In biplots the idea is to add information about the covariates to the PC graph.

Construction of biplots

The best two-dimensional approximation of data in an $n \times p$ matrix was determined by approximating the j^{th} observation vector $\underset{\sim}{x}_j$ in terms of the sample values of the first two PCs. The approximation is given by Equation 5:

$$\underset{\sim}{x}_j = \underset{\sim}{\bar{x}} + \hat{y}_{j1}\hat{e}_1 + \hat{y}_{j2}\hat{e}_2 \tag{5}$$

Where: $\underset{\sim}{\hat{e}}_1$ and $\underset{\sim}{\hat{e}}_2$ are the first two eigen vectors of $(n-1)S = x_c' x_c$. Where S denotes the contribution of the first principal component to the total variance, x_c' is the original observed data matrix, and x_c is equal to the mean corrected data with row vectors $(\underset{\sim}{x}_j - \underset{\sim}{\bar{x}})'$.

On the biplot, the eigen vectors $\underset{\sim}{\hat{e}}_1$ and $\underset{\sim}{\hat{e}}_2$ define the plane. The coordinates $\hat{y}_{j1}$ and $\hat{y}_{j2}$ for $j = 1, \ldots, n$, define the n units in that plane – principal component scores. The variables $x_1 \ldots x_p$ are positioned on the graph by the row vectors of $\hat{E} = [\underset{\sim}{\hat{e}}_1, \underset{\sim}{\hat{e}}_2]{:}p \times 2$, since:

$$\underset{\sim}{Y} = [Y_1\ Y_2] = [\underset{\sim}{\hat{e}}_1'\ \underset{\sim}{\hat{e}}_2'][x_1 : x_p] \tag{6}$$

The lengths of the vectors from x_1 to x_p were adjusted to ensure that all the variables were plotted on the same graph as the points $(\hat{y}_{j1}, \hat{y}_{j2})$; $j = 1, \ldots n$.

Assessment of goodness-of-fit

The study used five goodness-of-fit statistic tests to evaluate the fit-of-the-crash prediction models developed to the national rural road network – the Scaled Deviance (SD), Pearson Chi-Square (PCS), Scaled PCS (SPCS), Akaike's Information Criterion (AIC), Finite Sample Corrected AIC (AICc) and Bayesian Information Criterion (BIC) values. A summary of the goodness-of-fit measures of the road crash models developed is presented in Table 3.

The Generalised Poisson (GP) regression crash prediction models were found to be the best fit for the datasets compared to Negative Binomial (NB) models, due to their significantly lower AIC, AICc and BIC values generated. CPMs with negative AIC, AICc and BIC values have better performance compared to positive test values due to minimal information loss. Further, comparing the performance of the GP and NB models, the GP models generated higher values of the different residuals (SD, PCS and SPCS) than those generated by the NB models.

RESULTS

Crash model biplots

The model biplots developed by the study indicate the variance structure of the study

Table 3 Goodness-of-fit measures for all CPMs

Parameter	Goodness-of-fit[1, 2]			
	Negative Binomial Models		Generalised Poisson Models	
	CPM 1 (high-order rural roads)	CPM 2 (low-order rural roads)	CPM 1 (high-order rural roads)	CPM 2 (low-order rural roads)
Scaled Deviance (SD)	1 499.000	957.000	2 452.567	1 033.016
Pearson Chi-Square (PCS)	14.148	46.288	2 951.391	813.087
Scaled Pearson Chi-Square (SPCS)	1 499.000	957.000	4 618.773	1 669.331
Akaike's Information Criterion (AIC)	–2 715.819	–172.822	9 985.664	–1 417.109
Finite Sample Corrected AIC (AICc)	–2 715.671	–172.759	–9 985.499	–1 417.021
Bayesian Information Criterion (BIC)	–2 662.694	–148.503	–9 911.472	–1 387.927

1 Information criteria are in smaller-is-better form.
2 The full log likelihood function is displayed and used in computing information criteria.

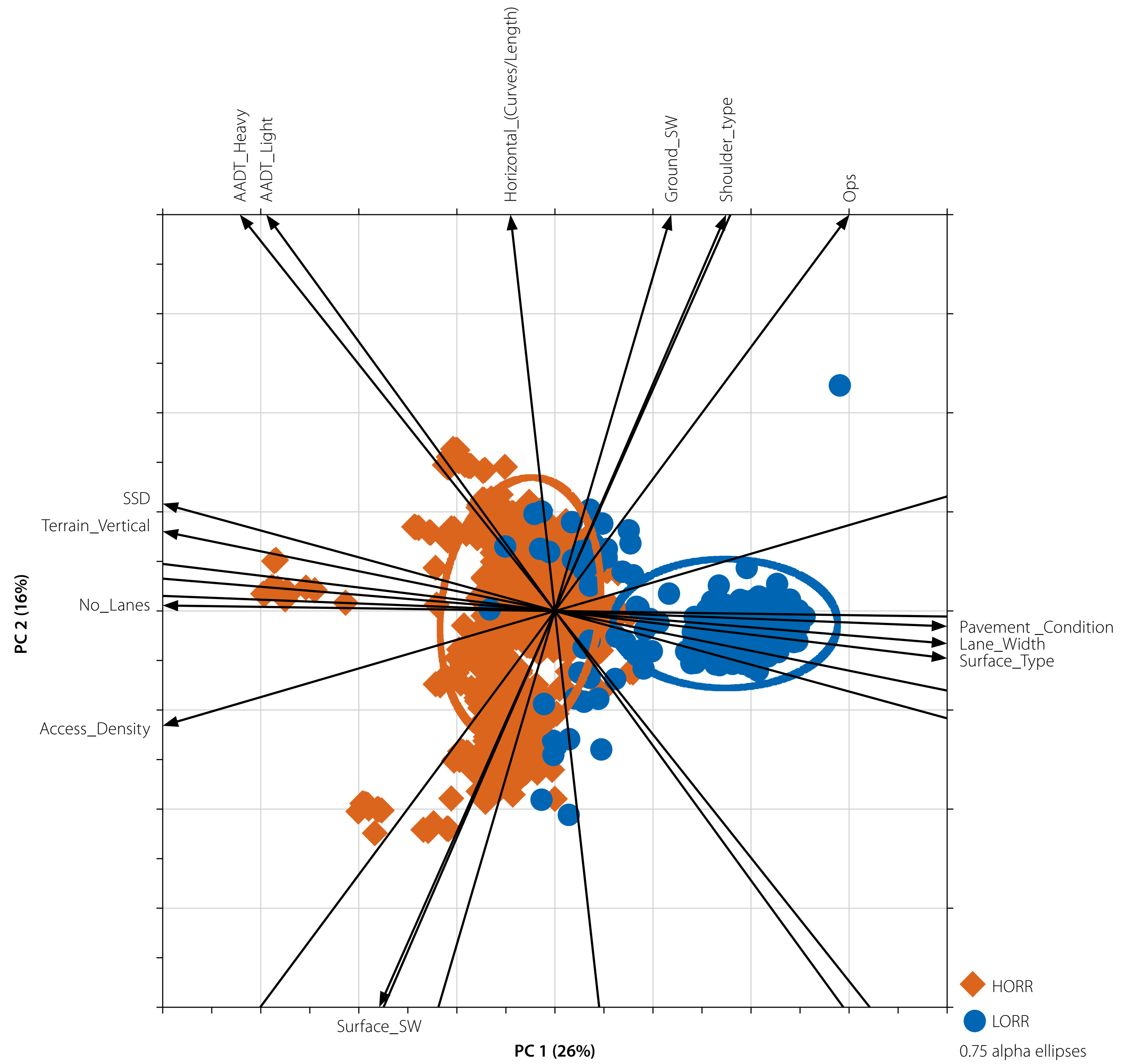

Figure 3 Principal component biplot

covariates for the entire rural road network dataset. The biplot generated in Figure 3 shows the projected observations (points) and the projected covariates (vectors) approximated by the first two principal components (PCs) shown in Table 4.

The PC biplot, represented graphically in Figure 3, describes the distribution and possible influence of the principal components on higher-severity crash levels on both road classifications – high-order rural roads (HORRs) and low-order rural roads (LORRs). The Principal Component Analysis (PCA) does not discard any covariates. Instead, it reduces the large number of dimensions by constructing PC plots (vectors and clusters). The PCs describe the variation and account for the varied

Table 4 Principal component summary

Principal component	Eigenvalues (all rural roads) Extraction: principal components			
	Eigenvalue	% Total variance	Cumulative eigenvalue	Cumulative (%)
1	3.676	26.257	3.676	26.257
2	2.240	15.999	5.916	42.256
3	1.337	9.549	7.253	51.805
4	1.221	8.721	8.474	60.525
5	1.104	7.885	9.577	68.411
6	0.865	6.180	10.443	74.590
7	0.859	6.138	11.302	80.728
8	0.714	5.102	12.016	85.830

influences of the covariates (Greenacre 2010). The PC plots thus indicate graphically how covariates correlate with each other. Specifically, the angles between the vectors inform how the covariates correlate with each other: when two vectors are close, forming a narrow angle (less than 90 degrees) this implies positive correlation (belonging to the same cluster group), while a wide angle (equal to or greater than 90 degrees) points to negative correlations (belonging to different cluster groups) (Greenacre 2010). Such influences can then be traced back from the PC plots using the developed crash prediction models to discern what produces the differences among the covariates and the covariate clusters (Acar & Yener 2009; Ginanjar *et al* 2017).

The first two PCs, represented by the cluster of dots, explain 26 percent (PC1) and 16 percent (PC2) of the variance contributed by the covariates on the different road classifications at an alpha ellipses level of 0.75 (see Figure 3). Without factoring in autocorrelation, the biplot gives an indication of which covariates are likely to explain the correlation with crash incidences. For the HORRs in the dataset, the model variance in PC 1 is potentially explained by:

- The widths of the surfaced shoulders (SSW).

The model variance for HORRs in PC 2 is potentially explained by:

- The access density (AD)
- The number of lanes on the HORR sections (NL)
- The hilliness of the vertical alignment (TV)
- The stopping sight distance (SSD) available to drivers on HORRs (SSD)
- The heavy and light vehicle annual average daily traffic (AADTH and AADTL)
- The number of horizontal curves per km on the road sections (Hor).

For the LORRs in the dataset, the biplot indicates that the model variance in PC 1 is potentially explained by:

- The width of the unpaved shoulder (GSW) on the LORRs
- The type of hard shoulder available on the LORR sections (ShoT)
- The 85th percentile operating speed (Ops).

The variance in the model for LORR sections in PC 2 is potentially explained by:

- The condition of the pavement surface on the LORRs (PC)
- The width of the available lanes (LW)
- The type of surface (paved or unpaved) on the LORRs (ST).

A detailed crash prediction model analysis (coefficient b* estimates) for the HORRs (CPM 1) and LORRs (CPM 2) is presented in the following section.

Crash prediction models estimates

The estimates (standardised regression coefficient b*) for all the Generalised Poisson Crash Prediction Models (GP-CPMs) developed and applied in this study to fit the datasets used – high-order rural roads (HORR) and low-order rural roads (LORR) – are summarised in Table 5. The crash prediction models tested all the study covariates, with the HORR GP-CPM eventually exhibiting the largest number (five covariates) of covariates showing statistically significant ($p < 0.05$) relationships with crash incidences. The CPM on LORR had four covariates that presented statistically significant associations with crash incidences.

Of the fourteen covariates tested in the models, seven covariates were found to exhibit statistically significant ($p < 0.05$) effects in the CPMs. The following seven covariates tested in all the crash prediction models that did <u>not</u> show any statistically significant affiliation with the crash incidences on the rural roads are:

1. The number of lanes available to traffic (NL)
2. The type of surface on the different road classifications (ST)
3. The proportion of hard shoulder surfaces (ShoT)
4. The number of horizontal curves per km length of rural road section (Hor)
5. The number of access points per km road section length (AD)
6. The condition of the pavement surface (PC)
7. The stopping sight distance available on the rural road sections (SSD).

Three covariates were shown to be influential ($p < 0.05$) in both CPMs, with varying effects (standardised coefficient b* estimates) on crash incidences. These covariates are: (1) the operating speed (Ops) on the road sections, (2) the vertical terrain – hilliness (TV), and (3) the ground shoulder width (GSW) on the road sections (all indicated in red in Table 4). The 85th percentile operating speed exhibited positive association with crash incidences in both CPM 1 (0.032) and CPM 2 (0.049). Similar to the operating speed, the hilliness of the vertical alignment exhibited a positive association to crash incidences on all rural road classifications (CPM 1 b* = 0.112; CPM 2 b* = 0.066). The ground shoulder width (GSW) demonstrated statistically significant relations to crash incidences in both CPM 1 and CPM 2. In CPM 1, the GSW covariate indicated a positive relation to crash incidences, with a 0.108 coefficient b* estimate. In contrast, the GSW covariate in CPM 2 indicated a negative relation to

Table 5 Best-fit Road Crash Prediction Models (GP-CPMs) performance

Tested parameters	Standardised regression coefficient (coefficient b*)	
	CPM 1 High-order rural roads	CPM 2 Low-order rural roads
AADT_Heavy (AADTH)	0.682	–
85th Percentile Speed (Ops)	**0.032**	**0.049**
Lane Width (LW)	0.137	–
Surface_SW (SSW)	–	–0.138
Terrain_Vertical (TV)	**0.112**	**0.066**
AADT_Light (AADTL)	–	0.315
No_Lanes (NL)	–	–
Surface_Type (ST)	–	–
Shoulder_Type (ShoT)	–	–
Ground_SW (GSW)	**0.108**	**–0.205**
Horizontal_(Curves/ length) (Hor)	–	–
Access_Density (AD)	–	–
Pavement_Condition (PC)	–	–
SSD	–	–

crash incidences, with a –0.205 coefficient b* estimate.

Two covariates exhibited statistically significant ($p < 0.05$) parameter estimates in CPM 1 only. These covariates are: (1) the proportion of heavy vehicles in the annual average daily traffic (AADTH), and (2) the width of the rural road lanes (LW). The proportion of heavy vehicles in the traffic stream (AADTH) covariate demonstrated positive associations with the crash incidences. The standardised regression coefficient b* for the AADTH covariate is 0.682. The model results also indicate that the lane widths (LW) are positively related (b* = 0.0.137) to the crash incidences on higher-order rural roads. Two other covariates emerged with statistically significant coefficient b* estimates on lower-order rural roads (CPM 2). These covariates are: (1) the surfaced shoulder width (SSW) and (2) the proportion of light vehicles in the annual average daily traffic (AADTL) on the road sections. The SSW was identified to have a negative relation (b* = –0.138) with crash incidences in CPM 2 while the AADTL exhibited a positive relation (b* = 0.315) to crash incidences.

DISCUSSION

The study developed novel crash prediction models for both classes of national rural road classifications in Namibia – high-order rural roads (HORR) and low-order rural roads (LORR). The results of the crash prediction models developed provide a platform to further link and examine the impact of road and traffic characteristics on driver behavioural traits and their distribution across the national rural road network. The study found several positive associations between road characteristics and fatal- and serious-injury crashes. In particular, hilliness, wide travel lanes, higher proportions of heavy vehicles (HVs) on higher-order roads and of light vehicles (LVs) on lower-order roads, operating speed and shoulder widths. Possibly more interesting is the fact that combinations of these factors resulted in a higher likelihood of fatal and serious injury crashes. Thus, for example, on higher-order roads, while the proportion of HVs had the highest individual impact, its impact was increased when the road was hilly, also where there were wider shoulders or higher operating speeds. Of course, the combined effect of multiple factors makes sense, as each of these elements individually has the potential to influence the level of attention that a driver needs to be paying to make sense of the road environment, and to 'read' the road cues safely. Where multiple factors need to be interpreted, cognitive overload is more likely to occur, and driver misperceptions are likely, which can in turn lead to driver errors and misjudgements.

The positive impact of hilliness, or the effect of vertical alignment on crash occurrence, is interesting, as it is a factor that appears to be largely innocuous unless it exists in combination with other factors, as found in the study. While several previous studies found no significant correlation between hilliness as a single variable with the occurrence of road crashes (Bester & Makunje 1998; Taylor *et al* 2002; Gitelman *et al* 2016), sites demonstrating a combination of hilliness and bendiness have been found to experience an elevated frequency of road crashes (Wang *et al* 2013; Ambunda 2018). This has been generally attributed to poor coordination between the horizontal and vertical alignment, leading to poor driver perceptions and driving errors (Bester & Makunje 1998; Walmsley *et al* 1998; Hanno 2004; Laird *et al* 2010). Such previous research thus supports the study finding in this research, that hilliness can be a significant contributor to crash risk when it occurs in combination with other road design and traffic parameters.

The results from CPM 1 found that an increase in the width of the travel lanes was associated with a higher occurrence of FSI crashes, when it occurs in combination with other road design and traffic parameters. On Namibia's high-order rural roads, lane widths are mostly wide (LW > 3.5 m) with extremely narrow (SSW < 1.5 m) or zero surfaced shoulder widths (Ambunda 2018). Previous research tells us that higher lane widths and longer forward visibility are both associated with increased speed, as drivers feel more comfortable with the available space ahead of them (Warrd *et al* 2004; Ma *et al* 2009; Liu *et al* 2016). Typically, the higher widths are also associated with high levels of lateral lane deviations. In the local Namibian context, the Namibian National Road Safety Council has already identified higher levels of same-direction road crash frequency where there are wide lanes present (NRSC 2012; Nghishihange 2018). While higher speeds may directly affect crash injury levels, it is likely the higher number of crashes themselves are precipitated through merging manoeuvres, brought about by greater speed differentials.

Another important finding of the study is the influence of the higher proportion of heavy vehicles (HV) and light vehicles (LV) in the traffic stream on the safety of road users on the different selected national rural roads. The novel models demonstrated that an increase in the volume proportion of HVs and LVs, in combination with other factors, increased the occurrence of FSI crashes on HORRs and LORRs respectively. The effect contributed by this modal split may partly be attributed to the speed variance between vehicles on high-speed highways (Gargoum & El-Basyouny 2016), as well as the fact that delays caused by slow-moving vehicles have been shown to increase the potential for risky overtaking behaviour by drivers of faster vehicles (Li *et al* 2020; Huang *et al* 2018; Emo *et al* 2016). Both of these elements are likely to be more pronounced on HORRs, where speed is a motorist priority, than on LORRs. Another possible contributing factor in the Namibian context is that HV drivers often drive long distances. Lack of quality sleep and severe fatigue are significantly associated with more frequent human errors (Aworemi *et al* 2010; Gastaldi *et al* 2014). Fatigue itself is difficult to measure and to prove as a contributory cause in crashes, but even so, should not be overlooked as a potentially important element in explaining the relationship between HV presence and high severity crashes on HORRs.

The operating speed of a road is of course fundamental to the incidence of crashes, with research showing conclusively that more crashes occur with increasing operating speeds (Bamdad & Mirbaha 2018; Wang *et al* 2018). This study found that operating speed demonstrated a statistically significant positive association with the occurrence of FSI crashes in all the CPMs, an effect that was magnified when high operating speeds co-existed with several road design and traffic factors. The study findings corroborated previous studies on the impact of operating speeds on Namibian national roads (Ambunda 2018; Ambunda & Sinclair 2019).

The study found that the ground shoulder width (GSW) had dissimilar but statistically significant influences on high-order and low-order national rural roads when combined with several factors. On high-order rural roads, the model demonstrated that ground shoulder widths in this study had a positive association with FSI crash frequencies. International research has produced mixed findings on the impact of wide hard shoulders on traffic safety (Stamatiadis *et al* 2009; Summala 1996; Knuiman *et al* 1993), but there is consensus regarding the role of the hard shoulder type itself. Paved shoulders are overwhelmingly shown to be safer than unpaved shoulders on higher-order roads (Ogden 1997; Hallmark *et al* 2009). As such, road managers in Namibia are more likely to see improvements in safety through the paving of gravel shoulders, rather than by increasing shoulder widths. On low-order rural roads – mostly low-volume paved roads or one-lane gravel roads – the ground shoulder width, in combination with other factors, demonstrated a negative correlation to the occurrence of FSI road crashes. This finding in the study suggests that an increase in the width of the ground shoulder on LORRs may have the potential to reduce crash frequencies. This confirms the findings of a study by Ambunda (2018), that ground shoulder widths on low-order rural roads are mostly non-compliant with design guidelines (existing GSW < Technical Recommendations for Highways 17 (TRH 17) GSW), so increasing the GSW to bring them in line with design standards could reduce crash frequencies. Driver speed selections tend to be lower on roads with gravel shoulders due to visual cues (colour difference between the paved roadway surface and the gravel-surfaced shoulder) that give a perception of a narrower driving lane. The finding on the impact of GSW on low-order rural roads also corroborates results from several international researchers (Zegeer *et al* 1987; Gitelman *et al* 2019).

The surfaced shoulder width (SSW) demonstrated a negative association with the frequency of FSI road crashes on lower-order rural roads (CPM 2) when combined with other design and traffic factors. This means that increasing the width of paved shoulders on road sections could result in a reduction in road crashes. This finding goes hand in hand with the design compliance finding, where existing SSWs were found to be significantly non-compliant (existing SSW < recommended TRH 17 SSW) with design guidelines. International research has confirmed that drivers tend to select lower speeds on narrow travel lanes (LW < 3.2 m) with narrow surfaced shoulders (SSW < 1.5 m) due to the perception of lower safety (Karlaftis & Golias 2009; Martens *et al* 1997; Godley *et al* 2004).

Arguably, in the local Namibian context, the combination of narrow shoulders and wider travel lanes (LW > 3.5 m) may be encouraging drivers to select high speeds due to a false sense of security and perceived space to correct driving errors. Despite the wider lanes on the Namibian national road network (Ambunda 2018), the narrow shoulder could also inadvertently lead drivers to steer away from the left shoulder and drive more closely to the centre of the rural road – this is a phenomenon found in previous research (Liu *et al* 2016; Ambunda & Sinclair 2019). In such a case, the likelihood of head-on crashes increases significantly. High levels of head-on crashes have been confirmed by crash statistics from the Namibian National Road Safety Council (NRSC 2012).

International standardisation of geometric design elements tends to give us confidence that roadway design features have been designed as safely as possible. However, given that there are over 1.3 million deaths each year on roads that largely conform to such standards, it would appear that there may well be room for improvement. Moreover, whether a road is used safely by drivers often comes down to the behaviour that the driver believes to be expected, based on his or her reading of the road design. In looking at possible reasons for the relationships between the covariables most significantly associated with increased crash risk in this study, it is apparent that those elements that appear to have the highest direct impact on safety levels are those that potentially mislead the driver (e.g. into thinking they are safer than they are: wider lanes and higher speed limits may be examples here) or those that create an element of surprise (e.g. combined hilliness and bendiness) or a degree of ambiguity about what is expected or safe.

CONCLUSION AND RECOMMENDATIONS

The study developed novel crash prediction models (CPMs) for the various road classifications on the Namibian national rural road network. The method developed predicts crash likelihood in the future for Namibian roads, by recognising which factors, and importantly, which combinations of factors, have historically led to higher crash occurrence. The study results showed that individual safety standards are potentially less effective when multiple factors co-exist, therefore leading to more research being required to develop improved standards that recognise that factors seldom exist in isolation, and account for the impact of high-cognitive loading on road users.

The insights from the study will also contribute to the United Nations global road safety performance targets, specifically those targets which focus on safer roads and road environments for all road users, based on high technical/design standards with reference to road safety and incorporating safe-system principles. Using the existing rural road design data as the key cog in the CPMs, the models developed are also intended to supplement and potentially replace traditional road safety tools which are typically dependent on high-quality and timely crash reporting. The models' application and insights could expand the road safety stakeholder's ability to determine road sections with potential crash risk and eliminate the risk for road users. These CPMs are novel in that they quantify the operational characteristics of the roads at existing high-crash locations, and identify elements that apparently contribute to elevated crash risk, either because they mislead the driver or because they create an element of surprise and ambiguity on the road. The CPMs also present an opportunity to examine, through before and after studies, the impact of the road environment on human-centred crash risk factors by comparing the changes that may result from road characteristic improvements.

The replication and applicability of the models at an aggregated level in countries with similar rural road environments will need to be investigated further for comparison purposes, as the models are predicated on accurate road design and traffic data, which may not always be present. However, such data is arguably easier to collect and corroborate than detailed crash data, which is notoriously unreliable in many parts of the developing world. The models present an opportunity to identify (and treat) potential high-risk locations for high-severity crashes, based primarily on geometric and traffic data, using reliable and accurate crash histories. This is a practical and more proactive alternative to the traditional process of waiting for a serious crash problem to develop and addressing it after the fact.

DECLARATION OF INTEREST

None

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REFERENCES

Acar, E & Yener, B 2009. Unsupervised multiway data analysis: A literature survey. *IEEE Transactions on Knowledge and Data Engineering*, 21(1): 6–20. DOI: 10.1109/TKDE.2008.112.

Ambunda, R 2018. Analysis of the relationship between fatal rural road crashes and road design elements: *Namibian case study*. Master's Dissertation. Stellenbosch University.

Ambunda, R & Sinclair, M 2019. Effect of two-lane two-way rural roadway design elements on road safety. *International Journal of Innovative Technology and Exploring Engineering*, 8(4): 632–637.

Aworemi, R J, Abdul-Azeez, A I, Oyedokun, J A & Adewoye O J 2010. Efficacy of drivers' fatigue on road accidents in selected southwestern states of Nigeria. *International Business Research*, 3(3): 225–233.

Bamdad, M B & Mirbaha, B 2018. Evaluating the relationship between operating speed and collision frequency of rural multilane highways based on geometric and roadside features. *Civil Engineering Journal*, 4(3): 609. DOI: 10.28991/cej-0309120

Ben-Bassat, T & Shinar, D 2011. Effect of shoulder width, guardrail and roadway geometry on driver perception and behaviour. *Accident Analysis & Prevention*, 43(6): 2142–2152.

Bester, C J & Makunje, J A 1998. The effect of rural road geometry on safety in southern Africa. *Proceedings*, International Symposium on Highway Geometric Design Practices, 30 August – 1 September 1995, Boston, MA, pp 1–10.

Bongiorno, N, Bosurgi, G, Pellegrino, O & Sollazzo G 2017. How is the driver's workload influenced by the road environment? *Procedia Engineering*, 187: 5–13. DOI: 10.1016/j.proeng.2017.04.343.

Chambers, R L 2000. Winsorisation for identifying and treating outliers in business surveys. *Proceedings*, 2nd International Conference on Establishment Surveys, 17–21 June 2000, Buffalo, NY, pp 717–726.

Chatterjee, S & Mitra, S 2019. Safety assessment of two-lane highway using a combined proactive and reactive approach: Case study from Indian national highways. *Transportation Research Record*, 2673(7).

CSRA (Committee of State Road Authorities) 1988. *TRH 26: Road Classification and Access Management*. Pretoria: CSRA.

Deller, J 2013. The influence of road design speed, posted speed limits and lane widths on speed selection: a literature synthesis. *Proceedings*, Australasian Transport Research Forum, 2–4 October 2013, Brisbane, Australia.

Denis, D 2021. Multiple linear regression. In Denis, D (Ed). *Applied Univariate, Bivariate, and Multivariate Statistics using Python*. New York: Wiley, 232–285.

Eenink, R, Reurings, M, Elvik, R, Cardoso, J, Wichert, S & Stefan, C 2005. Accident prediction models and road safety impact assessment: Recommendations for using these tools. *Sustainable Development, Global Change & Ecosystem*, 506184: 1–20.

Eggleston, Z, Hansen, P & Carrera, F 2016. *Improvement of road safety: Route-based assessment on major roads in Namibia*. Worcester, MA: Worcester Polytechnic Institute.

Emo, K, Matthews, G & Funke, G J 2016. The slow and the furious: Anger, stress and risky passing in simulated traffic congestion. *Transportation Research Part F: Traffic Psychology and Behaviour*, 42: 1–14.

Field, A 2013. *Discovering Statistics using IBM SPSS Statistics*, 4th ed. London: SAGE.

Fitzpatrick, C D 2014. *The effect of roadside elements on driver behaviour and run-off-the-road crash severity*. Master's Dissertation. Boston, MA: University of Massachusetts.

Gargoum, S A & El-Basyouny, K 2016. Exploring the association between speed and safety: A path analysis approach. *Accident Analysis & Prevention*, 93: 32–40. DOI: 10.1016/j.aap.2016.04.029.

Gastaldi, M, Rossi, R & Gecchele, G 2014. Effects of driver task-related fatigue on driving performance. *Procedia – Social and Behavioural Sciences*, 111: 955–964. DOI: 10.1016/j.sbspro.2014.01.130.

Ghanbari, A 2017. *Impact of pavement condition indicators on road safety in New Brunswick*. Master's Dissertation. Fredericton, NB: University of New Brunswick.

Ginanjar, I, Pasaribu, U S & Indratno, S W 2017. A measure for objects clustering in principal component analysis biplot: A cause study in inter-buses maintenance cost data. *Proceedings*, American Institute of Physics Conference, 1827(3). DOI: 10.1063/1.4979432.

Gitelman, V, Pesahov, F, Carmel, R & Bechor, S 2016. The identification of infrastructure characteristics influencing travel speeds on single-carriageway roads to promote self-explaining roads. *Transportation Research Procedia*, 14(6): 4160–4169. DOI: 10.1016/j.trpro.2016.05.387.

Gitelman, V, Doveh, E, Carmel, R & Hakkert, S 2019. The influence of shoulder characteristics on the safety level of two-lane roads: A case study. *Accident Analysis & Prevention*, 122(2): 108–118. DOI: 10.1016/j.aap.2018.10.003.

Glavić, D, Mladenovic, M N, Stevanovic, A, Tubic, V, Milenkovic, M & Vidas, M 2016. Contribution to accident prediction models development for rural two-lane roads in Serbia Mark. *Promet-Traffic & Transportation*, 28(4): 415–424. DOI: 10.7307/ptt.v28i4.1908.

Godley, S T, Triggs, T J & Fildes, B N 2004. Perceptual lane width, wide perceptual road centre marking and driving speeds. *Ergonomics*, 47: 237–256. DOI: 10.1080/00140130310001629711.

Gower, J, Lubbe, S & Le Roux, N 2011. *Understanding Biplots*. New York: Wiley. DOI: 10.1002/9780470973196.ch10.

Greenacre, M 2010. Biplots in practice. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 51(4): 375–392. DOI: 10.1111/j.1467-985x.2012.01069_5.x.

Hallmark, S L, McDonald, T J, Tian, Y & Andersen, D J 2009. *Safety benefits of paved shoulders*. InTrans Project 05–239. Ames, IA: Iowa State University.

Hanno, D 2004. *Effects of the combination of horizontal and vertical alignments on road safety*. MSc Dissertation. Vancouver: University of British Columbia.

Hauer, E 2014. Statistical Road Safety Modelling. *Transportation Research Record*, 1897(1): 81–87. DOI: 10.3141/1897-11.

Hicks, S & Fetter, M 1991. *An evaluation of robust estimation techniques for improving estimates of total hogs*. Fairfax, VA: US Department of Agriculture.

Huang, Y, Sun, J & Zhang, L H 2018. Effects of congestion on drivers' speed choice: Assessing the mediating role of state aggressiveness based on taxi floating car data. *Accident Analysis & Prevention*, 117: 318–327.

Ihueze, C & Onwurah, U O 2018. Road traffic accidents prediction modelling: An analysis of Anambra State, Nigeria. *Accident Analysis & Prevention*, 112(12): 21–29. DOI: 10.1016/j.aap.2017.12.016.

Karlaftis, M G & Golias, I 2009. Impacts of roadway condition, traffic and manmade features on road safety. *International Journal of Civil Engineering & Technology*, 4(7): 19–25. DOI: 10.1061/(ASCE)HY.1943-7900.0000746.

Knuiman, M W, Council, F M & Reinfurt, D W 1993. Association of median width and highway accident rates. *Transportation Research Record*, 1401: 70–82.

Laird, J, Harris, R & Shen, S 2010. *Accidents on rural roads – For better or worse*. University of Leeds, UK.

Li, G, Lai, W, Sui, X, Li, X, Qu, X, Zhang, T & Li, Y 2020. Influence of traffic congestion on driver behaviour in post-congestion driving. *Accident Analysis & Prevention*, 141: 105508.

Liu, S, Wang, J & Fu, T 2016. Effects of lane width, lane position and edge shoulder width on driving behaviour in underground urban expressways: A driving simulator study. *International Journal of Environmental Research and Public Health*, 13(10): 1–14. DOI: 10.3390/ijerph13101010.

Ma, Y, Yang, X & Zeng, Y 2009. Association analysis of urban road free-flow speed and lane width. *Tongji University Journal*, 37: 1621–1626.

Martens, M, Comte, S & Kaptein, N 1997. *The effects of road design on speed behaviour: A literature review*. Crowthorne, UK: Transport Research Laboratory. https://trid.trb.org/view/634567.

Murthy, N & Rao, R S 2015. Development of a model for road accidents based on intersection parameters using regression models. *International Journal of Scientific & Research Publications*, 5(1): 1–8.

Nghishihange, S 2018. *Factors contributing to motor vehicle accidents and severity of related injuries in Oshana region, Namibia*. Master's Dissertation. Windhoek: University of Namibia. DOI: 10.22201/fq.18708404e.2004.3.66178.

Noland, R B & Oh, L 2004. The effect of infrastructure and demographic change on traffic-related fatalities and crashes: A case study of Illinois county-level data. *Accident Analysis & Prevention*, 36(4): 525–532. DOI: 10.1016/S0001-4575(03)00058-7.

NRSC (Namibia National Road Safety Council) 2012. *Road accidents in Namibia – Statistical report 2012*. Windhoek, Namibia. DOI: 10.1017/CBO9781107415324.004.

Ogden, K W 1997. The effects of paved shoulders on accidents on rural highways. *Accident Analysis & Prevention*, 29(3): 353–362.

Oppong, R A 2012. *Statistical analysis of road accidents fatality in Ghana using Poisson regression*. Master's Dissertation. Kumasi, Ghana: Kwame Nkrumah University of Science and Technology.

Reifman, A & Keyton, K 2010. Winsorise. *Encyclopaedia of Research Design*, 1636–1638.

Stamatiadis, N, Pigman, J, Sacksteder, J, Ruff, W & Lord, D 2009. *Impact of shoulder width and median width on safety.* Washington, DC: Transportation Research Board, National Cooperative Highway Research Program (NCHRP), Report No 633.

Starkey, P, Riehle, E B & Ambunda, R 2017. Promoting rural access and mobility in northern Namibia: An integrated approach. *Proceedings*, 8th Africa Transportation Technology Transfer Conference, 8–10 May 2017, Livingstone, Zambia. Available at: **https://www.researchgate.net/publication/318680016**.

Summala, H 1996. Accident risk and driver behaviour. *Safety Science*, 22: 103–117. DOI: 10.1016/0925-7535(96)00009-4.

Taylor, M C, Lynam, D A & Baruya, A 2000. *The effects of drivers' speed on the frequency of road accidents.* TRL Report 421. Crowthorne, UK: Transport Research Laboratory. **https://trid.trb.org/view/651648**.

Taylor, M C, Baruya, A & Kennedy, J V 2002. *The relationship between speed and accidents on rural single-carriageway roads*. TRL Report 511. Crowthorne, UK: Transport Research Laboratory. **http://www.safespeed.org.uk/TRL511.pdf**.

Turner, B, Woolley, J & Cairney, P 2015. An analysis of driver behaviour through rural curves: Exploratory results on driver speed. *Proceedings*, Australasian Road Safety Conference, 14–16 October 2015, Queensland, Australia, Vol 10, pp 1–10.

Vaa, T 2014. From Gibson and Crooks to Damasio: The role of psychology in the development of driver behaviour models. *Transportation Research Part F: Traffic Psychology and Behaviour*, 25(Part B): 112–119. DOI 10.1016/j.trf.2014.02.004.

Walmsley, D A, Summersgill, I & Binch, C 1998. *Accidents on modern rural single-carriageway trunk roads.* TRL Report 336. Crowthorne, UK: Transport Research Laboratory.

Wang, C, Quddus, M A & Ison, S G 2013. The effect of traffic and road characteristics on road safety: A review and future research direction. *Safety Science*, 57: 264–275. DOI: 10.1016/j.ssci.2013.02.012.

Wang, B, Hallmark, S, Savolainen, P & Dong, J 2018. Examining vehicle operating speeds on rural two-lane curves using naturalistic driving data. *Accident Analysis & Prevention,* 118(4): 236–243. DOI:10.1016/j.aap.2018.03.017.

Warrd, D, Steyvers, F J & Brookhuis, K A 2004. How much visual road information is needed to drive safely and comfortably. *Safety Science*, 42: 639–655. DOI: 10.1016/j.ssci.2003.09.002.

WHO (World Health Organization) 2018. *Global status report on road safety 2018.* Geneva, Switzerland.

Zegeer, V C, Reinfurt, D W, Hummer, J, Herf, L & Hunter, W 1987. *Safety effects of cross-section design for two-lane roads.* Chapel Hill: University of North Carolina, Highway Safety Research Centre.