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Exploring Crash Risk Factors Associated with Drivers in Saudi Arabia

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ABSTRACT

The traffic safety in roads depicts "the procedures implemented and actualized to inhibit drivers and operators from being killed or significantly wounded". In this study, the random Poisson-parameters regression-model is adopted and implemented in order to realize, measure, test, and compare driving-behaviours throughout three main cities in Saudi Arabia, i.e., Makkah, Dammam and Riyadh. The methodology focuses on optimizing decision-making and insights to influence legislators and key decision-makers to manage the future needs for roads in Saudi Arabia. The random parameters regression has been used to predict the number of crashes that result from external locus of control, driving-behaviour, time, and location within three main cities/regions in the Kingdom of Saudi Arabia (KSA). The study identified that the number of crashes increase among drivers who show aggressive behaviour and decrease among drivers with more violations. Night-time (period from 12:00 am until 6:00 am) has also been shown as a risk factor for car crashes. The study recommends that drivers who were frequently involved in car crashes may complete a driving improvement program so that their aggressive tendencies would be controlled. Also, visible traffic law enforcement at night could help prevent the higher number of crashes occur at that time.

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1. Introduction

All over the Kingdom of Saudi Arabia (KSA), motor vehicles are the primary mode of transport between regions and cities. More than six-million motor vehicles navigate the highways of the KSA (Alhazmi, 2019; Mansuri et al., 2015). Historical data denotes that road traffic crashes victims represent 20% of the intake patients at medical-related institutions within the KSA, and 81% of the casualties, at these institutions, are a consequence of road-traffic crashes (Mansuri et al., 2015). A total of 611,000 road-traffic crash victims and 86,000 road-traffic crash fatalities were over the past two decades. Furthermore, 7% of the road traffic crashes survivors subsequently became chronically disabled (Al-Naami et al., 2010; Saudigazette, 2013). Between 1997 and 2002, traffic crash fatalities within the KSA have increased by 31.6% for men and 1.3% for women. The aforementioned findings illustrate that the "Potential-Productive Years-Life" (PPYL) is larger in men than women (Alhazmi, 2019; Elshinnawey et al., 2008). Locus-of-Control (LOC) means the control of people over their lives. A person with external-LOC believes that he has no control over his/her life, while a person with internal-LOC believes that he can affect (control) his/her life.

As declared by earlier hypotheses, people with an external-LOC may believe that any crash involvement is as random as a throw of the dice (Rotter, 1966). The theory of LOC has proven useful in predicting and explaining human behaviour (Mali, 2013). Individuals, who own an internal LOC, have been shown to have lower risk to traffic crash (Huang, 2012).

The majority of the recent studies in road-traffic crash within the KSA concentrated on young drivers between the age of 18 and 24 years. Mohamed and Bromfield (2017) conducted a study to examine the connections between road-traffic crashes, driving behaviour, and undeveloped male motorists' mindsets regarding road traffic safety in the Eastern Region of the KSA, using "structural equation modelling" (SEM). The research employed a dataset of 287 drivers between the age of 18 and 24. The result showed that driving comportment of youthful Saudi male drivers is segmented into three separate types: error making, aggressiveness, and negligence. Distinct from error making (violations), both aggressive and negligent behaviours are substantially determined by the drivers' mindsets regarding road traffic safety, and both increase the risk of road traffic crashes.

This paper examines LOC and driving-behaviour of all age groups in the three main cities/regions in Saudi Arabia. Figure 1 shows the three regions with highest rate of road crash data.

Furthermore, the recent studies targeted drivers in general, while the present study focuses on drivers who have been involved in car crashes. This study explores the relation between perceived driving-behaviour and road-traffic crashes. The main objectives of this study are:

(i) To predict the number of crashes based on LOC and driving-behaviour in the three main cities/regions.

(ii) To predict the number of crashes based on the location and time of crashes in the three main cities/regions.

The research paper will provide value in regards to emphasize driving comportment and road safety concerns within the three regions of KSA that have an elevated number of traffic crashes. The research will examine the objectives using Random-Parameters Poisson regression-model. The research focused on the limited crash data between 2015 - 2017, before allowing the female-driving in KSA.

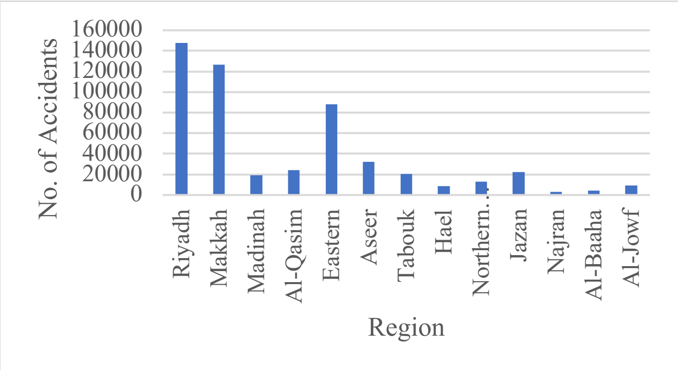

Figure 1: Traffic accidents (number) in different main cities in KSA in 1436H (*Source:* Ministry of Saudi-Interior, General-Directorate of Traffic)

2. Literature Review

Hassan (2016) examined the driving behaviour of 18 to 24 year old male Saudi motorists in the capital city of Riyadh using SEM. The study measured the relevant elements linked to the contribution of young Saudi motorists during at-fault road traffic crashes. The result showed that driving above the posted speed limit was the primary cause for youthful Saudi motorists attaining road traffic citations (73%). Also, 'running late' was the primary cause for being engaged in hazardous driving behaviours (62%), followed by assessing or checking the functionality or capabilities of the occupant's car or simply "showing off" (18%).

In 2016, the mindsets and hazardous behaviour of adolescent motorists in Riyadh have been investigated by Ramisetty-Mikler and Almakadma (2016). Approximately 40% of the respondents have participated in dangerous driving behaviour known as 'Tafhit', where it is called "Drift" which is a deliberate act of drifting cars. 51% of individuals who were previously involved in risky actions had also reportedly participated in 'Tafhit'. Seventy percent of those who consider 'Tafhit' a unique skill or a trending action were also involved in 'Tafhit'. Using a logistic multivariate regression, the authors concluded that motorists were enthusiastic about participating in risky conduct, even though they knew it was hazardous.

Arshad and Waleed (2020) conducted a research to study the risk factors for in traffic fatal crashes using neural network. They explore crash data between 2017 and 2019 from 15 highways in KSA. They concluded that the most sensitive variables to traffic crash are pedestrian involvement, volume of traffic, traffic speed, environmental condition types of vehicles and highways. Their results showed that the most contributable variables in crashes are: volume of traffic, traffic speeds, environmental conditions, pavement conditions vehicle and road type, and pedestrians' involvement.

Previous research studies when exploring road traffic crashes risk factors found that several factors contributed to road traffic crashes severities and frequencies occurrence such as vehicles, drivers, characteristics of roads and environmental condition (Arshad, 2020; Majedm, 2021; Reason et al., 1990; Roshandeh et al., 2016). Ahmed et al. (2020), also explore the causes of traffic crashes and concluded that the most leading traffic crashes causes are speeding, overtaking, wrong rotations.

A different study exemplifies the effect of motorist's particular traits and behaviour regarding road traffic crashes in the city of Tabuk. The goal of the study (Issa, 2016) was to understand exactly which factors are relevant for road traffic crashes in the study area (Tabuk city), and to statistically calculate the effect of certain motorist's unique traits on road traffic crashes. The study showed that motorists under the age of 30 were engaged in approximately 60% of the road traffic crashes, and more than 80% of the road traffic crashes were linked to human factors. Drivers with advance driving experience and advanced scholastic achievements have participated in more road traffic crashes than drivers without an advance driving and educational experience.

Driving-behaviour was examined by Al Reesi et al. (2013) through using a "driving behaviour questionnaire" (DBQ) on a sample of Omani University students. They used MLRA (multivariate-logistic regression-analysis). The following factors were determined by their study to be significant predictors of a person causing road-traffic crashes: driving-history, driving-familiarity, two DBQ variables – driving-related mistakes and reckless driving infringements.

Al-Hemoud et al. (2010) concentrated on motorists between the age of 25 and 35. The goal of their study was to assess the connection between standard of living and probability of road traffic crashes for male Kuwaiti motorists. The results indicate that motorists keep insufficient distance between their motor vehicles and the motor vehicles preceding them on Kuwait nationwide public roadways, which is a sign of reckless driving behaviour. Speeding was shown to be the most significant predictor of road traffic crashes.

There are existing gaps in traffic safety research. Recent studies (Alhazmi, 2019; Al-Hemoud et al., 2010; Al Reesi et al., 2013; Hassan, 2016; Issa, 2016; Mohamed & Bromfield, 2017; Ramisetty-Mikler & Almakadma, 2016) in the countries of the Gulf Cooperation Council (GCC) were all limited to certain levels of aggregation. For instance, the sample was limited to a certain university, age group, or city (see Table 1).

Table 1: Summary of past studies on driving-behaviour in accordance with the road-traffic crashes

Study	Focused group	Level of aggregation	Statistical method
Hassan, 2016	18 to 24 years	City	Structural Equation Model (SEM)
Ramisetty-Mikler and Almakadma, 2016	Adolescents	Schools	Logistic regression multivariate
Issa, 2016	Injured drivers	Hospitals within a city	Chi-Square test
Al Reesi et al., 2013	University students and staff	University	ANOVA logistic regression
Al-Hemoud et al., 2010	25 to 35 years	City	Stepwise procedure multiple correlation matrix
Mohamed and Bromfield, 2017	18 to 24 years	City	Structural Equation Model (SEM)

Previous research investigated some of these problems (effect of time, location of crash, driving-behaviour, and LOC on the chances of being involved in a car crash), but this is the first study in which the effects of driving-behaviour, LOC, and location and time of crashes are integrated to understand their relation with the number of crashes in the three different main regions in KSA.

3. Data and Empirical Setting

3.1 Population and Sample

Motorists who live in Makkah, Dammam and Riyadh, and have an official driving license were surveyed in this research on their driving habits and their sense of control over their actions on the road (NAJM). There was no need for law enforcement participation in any of the crashes examined in the research (fatalities, serious injuries). From 2015 to 2017, NAJM received 362,170 reports of road traffic crashes.

Equation 1 (Israel, 1992) was used to find the minimum number of samples required for this investigation, which was 383 with a 5% margin of error. A total of 362,170 drivers from Makkah, Dammam, and Riyadh were randomly chosen for this research, which included 700 of them. Because some individuals may not wish to participate, the calculated sample size was almost twice as large as the minimum sample size, which was set. Only 23 out of 383 surveys were rejected because they were not filled out correctly.

$$n = \frac{N}{1+N(e)^2} \tag{1}$$

Where, N = population size, n = sample size, e = level of precision (margin error).

3.2 Driving Behaviours and the Locus of Control for Various Demographics

As shown in Table 2, a breakdown of driving behaviours by age group can be shown. An increase in age was shown to decrease mean aggressor driving, although this decrease was not statistically significant ($F(3, 356) = 1.897$ and $p = 0.128$). $F(3, 356) = 0.877$ and $p = 0.453$) revealed a similar pattern in neglectful driving conduct. The only dependent variable for which the age groups varied was the driving behaviour violation ($F(3, 356) = 10.276$ and $p < 0.001$). Age groups exhibited no significant differences in the control area ($F(3, 356) = 0.622$ and $p = 0.601$).

Figure 2 depicts the overall number of collisions, broken down by the time of day and geographic location. However, in Riyadh and Dammam, the bulk of the road traffic crashes happened between 12:00 pm and 6:00 pm, respectively, while in Makkah, the percentages were almost the same.

Figure 3 depicts the frequency of traffic crashes in each area at various locations. Regardless of the area, most road traffic crashes happened on the city's main thoroughfares. In certain places, there are more highways than in others, which may explain why there is a disparity in the number of road traffic crashes.

Table 2: Descriptive statistics for driving behaviour and locus of control among different age groups

Age group	N	Aggressiveness		Negligence	
		M	SD	M	SD
18 - 24	67	2.074	0.586	1.798	0.488
20 - 30	91	1.926	0.52	1.73	0.476
30 - 40	113	1.908	0.509	1.683	0.445
40 and above	89	1.893	0.476	1.724	0.438
Where: N = Number of observations, M = Mean and SD = Standard deviation					

Continued on next column

Table 2: *Continued from previous column*

Age group	Violation		Locus of control	
	M	SD	M	SD
18 - 24	1.981	0.473	2.712	0.551
20 - 30	1.785	0.551	2.722	0.542
30 - 40	1.803	0.452	2.717	0.544
40 and above	1.553	0.469	2.628	0.525
Where: N = Number of observations, M = Mean and SD = Standard deviation				

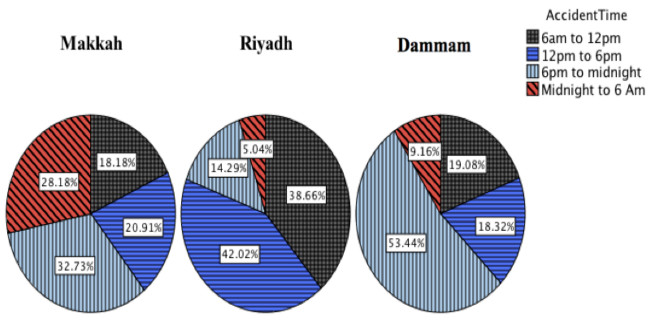

Figure 2: The percentage of time of crashes for drivers in each region

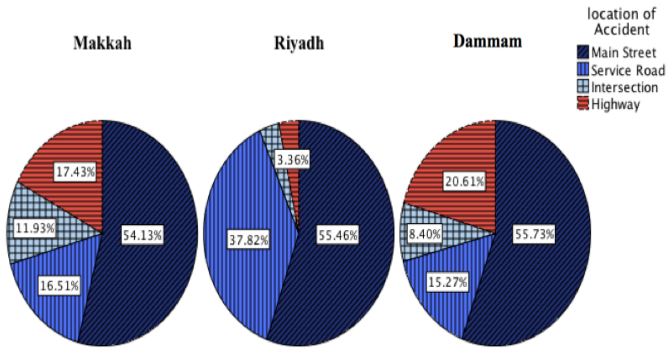

Figure 3: The percentage of location of crashes for drivers in each region

4. Methodology

4.1 Demographic Information

During the survey, 18 questions were used to investigate demographic and road traffic collision data to compare and validate the official reports. Two questionnaires were used to measure driving behaviour and locus of control: the "driving behaviour questionnaire" and the "T-LOC." The demographic data included age, gender, marital status, and income. Also included in the data was information on the location where a road traffic collision occurred and how many passengers were in a vehicle when it collided with another vehicle.

4.2. Driving Behaviour Questionnaire (DBQ)

Based on the Manchester "driving behaviour questionnaire" (DBQ) adapted for this study, a survey was administered to obtain the respondents' ideas about their driving habits. The DBQ self-report survey has been utilised in numerous exploratory investigations to assess drivers' imbalanced driving behaviour (Elander et al. 1993; Sucha et al., 2014). The survey used in this research was tailored to the DBQ reproduction used in Finland and the Netherlands, which included 27 questions to gauge a driver's behaviour while behind the wheel (Lajunen et al., 2004). Lawton et al. (1997) and Parker et al. (1998) copied their DBQ extended 27-item version into Dutch and French along with four extra parts (lapses, errors, aggressive driving and ordinary violations). Answers to the DBQ were given a point value from 1 to 6, with one representing "never" and six representing "almost often." Using a novel scale, the survey employed in this research was tailored to Saudi participants and focused on three essential components (violations, aggressiveness and negligence). The DBQ scale included 14 questions on the participants' driving habits.

4.3 Traffic Locus of Control Questionnaire

The “Traffic-Locus of Control” (T-LOC) Scale was adapted from the Multidimensional Traffic Locus of Control Scale (T-LOC), initially established by Ozkan and Lajunen (2005). Subsequently, only eight measures indicating external locus of control linked to driving behaviours were utilised in the present research. Multiple features of the Traffic Locus of Control Scale (T-LOC) are scored on a five-point scale (where, 1 is not at all possible; 5 is highly possible), and each item is evaluated on the presumed reason for why a road traffic collision happened (Ozkan & Lajunen, 2005).

4.4 Factor Analysis of DBQ

Principal Component Analysis (PCA) is a statistical procedure that employs an orthogonal transformation to turn a collection of potentially connected factors (principal components) into a collection of standardised linearly unrelated elements (Granato et al., 2018). PCA was used to the driving behaviour scale to confirm its theoretical factor structure, which is projected to have three elements (aggressive, violent and negligent) (Sucha et al., 2014). The responses of 360 residents from the KSA cities of Makkah, Riyadh and Dammam were assessed. The orthogonal rotation technique varimax was used, which uses the squared loadings modification to get significant coefficients. Two discrete criteria were used to determine the number of varied elements: Kaiser's eigenvalues criterion more critical than one (Kaiser, 1960) and a scree plot (Figure 4). Cronbach's Alpha for the internal consistency dependability of three DBQ components was determined to be 0.534 for negligence, 0.824 for aggressiveness, 0.658 for violations, and 0.799 in total for the three elements, indicating strong reliability for the components. Table 3 shows the number of features of each component.

4.5 Data Analysis Techniques

Several statistical approaches were applied to the data using the R software version. The research looked at the links between demographic information and driving behaviour, as well as the locus of control.

The initial goal was to forecast the number of crashes based on driving behaviour and locus of control. The Random Parameters Poisson regression was used to test this. As a result of the data being counted, the number of crashes is the dependent variable. Before constructing a regression model, over-dispersion and under-dispersion were explored to assess the adequacy of the Poisson distribution option.

Poisson regression is a kind of regression analysis used to model count data and contingency tables. This extended linear model posits that the dependent variable Y has a Poisson distribution and that a linear combination of specific parameters may be used to predict its anticipated logarithmic value (Akin, 2011).

A random-parameters Poisson regression model, in which the coefficients corresponding to the predictor variables are permitted to change, rather than be constants, has been proven the best match for crash data (Agbelie, 2016; Alhazmi, 2019).

The second goal was to forecast the number of collisions based on the time and location of the crashes. For fitting the data, both a Poisson regression and a Negative Binomial regression model were explored. The Poisson distribution presupposes that the mean and variance are identical, but the Negative Binomial distribution allows for various values (Stanojević et al., 2018).

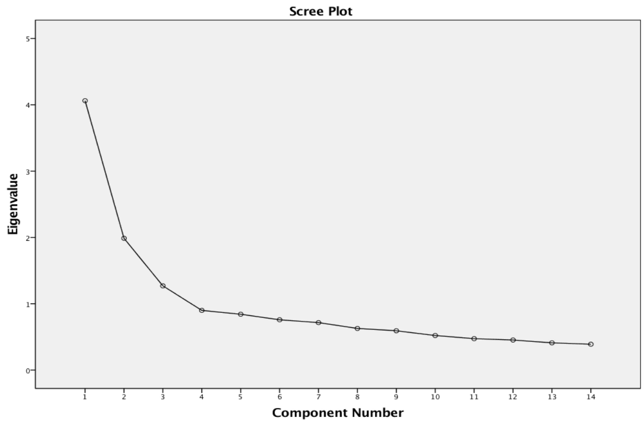

Figure 4: Scree plot for number of components in the Principal Component Analysis (PCA)

Table 3: Cronbach’s Alpha coefficient of reliability for three components of driving behaviour questionnaire (DBQ)

No.	Component	Number of items	Cronbach Alpha
1	Negligence (Lapses)	4	0.534
2	Aggressiveness	6	0.824
3	Violations	4	0.658
4	Total	14	0.799
Number of items = number of questions for each component in DBQ			

There was no indication of either under-dispersion or over-dispersion. Furthermore, since the Poisson model provided a more efficient model fit and model parsimony, it was utilised to assess the impact of the predictive parameters (time and location) on the dependent variable (crash location). There was, however, some indication of non-homogeneous variance. To accommodate for this, a Poisson regression model with random parameters was employed instead of the standard Poisson regression model, enabling the regression coefficients to fluctuate among data (Agbelie, 2014).

5. Results and Discussions

5.1 Predicting the Number of Crashes from the Driving Behaviours and External Locus of Control

Previously, a linear link between the frequency of collisions and driving behaviour had been demonstrated to be insignificant. As a result, the Poisson generalised linear model was used to forecast the number of crashes. The primary difference between the "Poisson linear model" (PLM) and the conventional "general linear model" (GLM) is that the GLM assumes a normal distribution for the dependent variable. In contrast, the PLM believes a Poisson distribution for the dependent variable. It is linked to the linear combination of predictors by a link function, often a logit function, in the same way, that logistic regression is. Furthermore, the Poisson model predicts that the variance of the counts will be about equal to their mean. Violation of this assumption is referred to be under-or over-dispersion, and it may be officially evaluated. This assumption was checked in the current research utilising the Cameron and Trivedi test (Cameron & Trivedi, 1990).

Random coefficients are allowed to be included in order to extend the standard Poisson model. As a result of not noticed heterogeneity, this extension of the model allows looking at the heterogeneity due to non-observable factors. Undoubtedly, factors not observed may lead to unstable transactions in the model. It is difficult to use all the factors that can lead to the best models. So, to solve this problem, random variables must be placed in the model to represent the predictions that have been omitted. It is done by allowing the special distribution of the unchanging coefficients. Several distributions be considered, since in this study a Poisson model was chosen for random coefficients with a Gaussian distribution of coefficients. Which provides more flexibility than the standard model, and is somewhat convergent with the negative binomial model for random coefficients

Halton's draws were used to estimate the random coefficients (Halton, 1960). As is well known, computer standard models usually generate numbers randomly for in algorithms for estimation such as integrals in estimation of Monte Carlo. However, to enhance the estimation process, more serial numbers in sequences like Halton's draws. In this study Halton's draws were used in each case with 201 draws (Agbelie & Roshandeh, 2014; Beck et al., 2011).

Table 4 presents the models result. Estimated parameter from RPM can vary with observations. Factors can be determined if it is random or not through the significance of SD. Therefore, it is significant If the estimated parameter standard deviation differs from zero, then it is random parameter. Otherwise, is fixed parameter. Table 4 shows that all results are significant for all standard deviations. When set the predictors to zero then the dependent variables will be represented by parameter estimated value.

Equation 2 was used to estimate the values of elasticity by calculate the marginal effects (Washington et al., 2003). When changes in dependent variable by 1%, then the changes of percentage of the dependent variable is called Elasticity.

$$E_{x_{ik}}^{\lambda_i} = \frac{\partial\lambda_i}{\lambda_i} \times \frac{x_{ik}}{\lambda x_{ik}} = \beta_k x_{ik} \quad (2)$$

Where, E = elasticity, λi = dependent variable frequency, βk independent variable parameter, xik = independent variable value.

Table 4: Parameters for predicting crashes number of SPM and RPM based on LOC and driving behaviours

Standard Poisson Model (SPM) parameters			
Variable description	Estimated parameter (SD)	t Statistic (SD)	Marginal effect
Constant	1.240***	5.539	
Average aggressive driving behaviour	0.157*	2.341	0.304
Average negligent driving behaviour	0.049	0.676	0.085
Average violations	-0.244***	-3.375	-0.432
Average LOC	-0.058	-0.959	-0.156
Random Poisson Model (RPM) Parameters			
Variable description	Estimated parameter (SD)	t Statistic (SD)	Marginal effect
Constant	1.239***	5.503	
Average aggressive driving behaviour	0.157* (0.001)	2.325 (0.017)	0.304
Average negligent driving behaviour	0.049 (0.001)	0.671 (0.19)	0.085
Average violations	-0.244*** (0.001)	-3.375 (0.014)	-0.432
Average LOC	-0.058 (0.002)	-0.959 (0.056)	-0.156
* = p < 0.05, *** = p < 0.001, SD = Standard deviation			

Comparison between SPM and RPM models has been done by conducting Wald test. The test results showed heterogeneity evidence of significant (p = 0.011) across the parameters. The test of ratio of log likelihood was carried out to determine the two superior models, using Equation 3 to find the test statistic.

$$\chi^2 = -2*(LL(\beta_{LM})) - (LL(\beta_{SM})) \quad (3)$$

Where, χ2 = test statistic, LL (βLM) = log likelihood for the model at a lower value of convergence and LL (βSM) = log likelihood for the model at a higher value of convergence (Agbelie, 2014; Washington et al., 2011).

With the degrees of freedom, the distribution of test statistic (χ2) was equal to the difference between estimated parameters number of the two compared models. For the SPM model, the LL at convergence is -665.694 (with 5 parameters), while for the RPM model, LL at convergence is -665.510 (with 10 parameters). Based on the test results there is no significant difference shown between the models, which means no one of the models is superior (χ2 (5) = 0.368).

The results show for both models an estimated parameter 0.157 for aggressive driver behaviour, while the estimated parameter SD value is 0.001 for the RPM. Also, for both models (SPM and RPM), the elasticity (marginal effect) of 0.304. It means that every increase by 1% aggressive driving behaviour score predicted crashes number will be increase by 0.304%. This indicates that people driving more aggressively they have more chances to involve in vehicle crashes. Similar result was found that aggressive driving behaviour has a higher chance to be involved in vehicle crashes (Mohamed & Bromfield, 2017) and on the other hand safer driving behaviour will involve in less number of crashes (Mirzaei et al., 2014).

An estimated parameter for negligent behaviour for both models (SPM and RPM) is 0.049, thus the results statistically are not significant for models. Similar research shows same results as negligent behaviour is not statistically significant for predicting traffic crashes DBQ (Al Reesi et al., 2013).

Negative relationship was found for violations with -0.244 estimated parameter both models. It was found that the SD for estimated parameter of RPM is 0.001. For both models the values of Elasticity is -0.432. This result showed that traffic crash numbers will be decreased by 0.432% if the violation score increased by 1%. This is an unexpected result which needs further explanation and research. One possible explanation is that drivers rely on experience and therefore feel more confident and commit violations. Of course, if this is true, then it is assumed that the accumulated years of driving experience and confidence are factors in reducing crashes, despite their repeated violations. Acknowledging the wrongdoing in the questionnaire may be the key thing. Also, the reason could be that the most experienced drivers did not hesitate and admitted to committing traffic violations. Some researchers found different results. They said that no violation impact on vehicle crashes (Mohamed & Bromfield, 2017). To clearly this relationship further research will be needed and conducted to determine if experience in driving correlates with telling the truth about committing violations. Moreover, if this interpretation of the current study is correct, then the driving with experience can be a factor between road crashes and violations, and accordingly it will be another way for future study.

An estimated parameter for both model in LOC gives -0.058 which is a non-significant result. Other researcher found that for vehicle crash rate the LOC is an important factor for prediction. (Huang, 2012).

5.2 Predicting Crashes Number from Crashes Location and Time

The same models as on objective one were used to assess the second objective of the study. The difference is using Equation 4 to calculate pseudo-elasticity taking into account the value of predictors either 1 or 0 (Washington et al., 2003). Table 5 shows the results for both models. The crashes' location and time were used as categorical predictors. Comparison between both RPM and SPM was done. For the RPM model a significant evidence of parameters heterogeneity was found when using Wald test ($p < 0.001$). The estimated parameters SD for variables' location were found not significant, which means the parameters were fixed across the model. While, for the variables time the SD were found significant, which means they random parameters.

$$E_{x_{ik}}^{\lambda_i} = \frac{e^{\beta_k - 1}}{e^{\beta_k}} \quad (4)$$

For the SPM model, the LL at convergence was found to be -663.591 (for 8 parameters), while for the RPM model, LL at convergence is -663.575 (for 16 parameters). Based on the test results there is no significant difference shown between the two models, which means there is no superior model is ($\chi2$ (8) = 0.016).

The results show that estimated parameters are not significant for the crash predictors location. The estimated parameters for SPM for highway, intersection, service road and main street, are 1.258, 1.124, 1.217, 1.241 respectively and for RPM are 1.259, 1.126, 1.216, 1.241 respectively. The p values for both models between 0.210 to 0.265. This statistical test result shows that there is no role of road type on the crash, although some researcher indicated that on the main roads the chance for occurring a crash will be increased (Alhazmi, 2019; Al-Ghamdi, 2002).

Comparison was made between early mooring period 12:00 am – 6:00 am and the rest three periods 6:00 pm – 12:00 am, 12:00 pm – 6:00 pm, and 6:00 am – 12:00 pm. The estimated parameter for both models in the time 6:00 am and 12:00 pm is -0.203, showing relationship with negative sign. The estimated parameter SD was found to be 0.007. For both models' pseudo-elasticity of -0.225 was found, which means that on this period of time during the day predicted crashes will be lesser by 0.225% relative to the category of reference.

An estimated parameter with a significant value of -0.308 (negative) for a period of 12:00 pm and 6:00 pm (for SPM and RPM models). For the RPM model the estimated SD is 0.006. The pseudo-elasticity for both models was found to be -0.361 indicating that the predication of crashes frequency at that period of the day lower by 0.361% from reference period 12:00 am – 6:00 am.

An estimated parameter with a non-significant value -0.186 was found for SPM model period 6:00 pm and 12:00 am and for RPM was found to be -0.194, although for SPM and RPM models the p values were found 0.068 and 0.07 respectively. The RPM has largest SD value among the variables of time (0.134).

The results show that crashes with highest rate occur during night period 12:00 am – 6:00 am, this can be as a result of tiredness and poor visibility. This could also due to others reasons such as low-density roads, no police enforcement, and lack of technologies (speed cameras, red light camera, surveillance cameras, and traffic control systems) may affect drivers' behaviour in the KSA to drive faster during night-time. Also, driving under the influence can be a major factor which leading to driving with careless and speeding. Further research and studies are required to investigate the reasons and factors of increasing crashes during this period of the day. Also, different counter measures could be taken into account, such as increasing fines, increasing number of cameras at night, improving visibility and road conditions. Research done in Riyadh revealing similar results, it shows that 60% of road crashes occur during night period (Hassan & Al-Faleh, 2013; Hassan et al., 2013).

Table 5: SPM and RPM models parameters for predicting crashes number from crashes location and time

Standard Poisson Model (SPM) parameters Standard Poisson Model (SPM) parameters			
Variable description	Estimated parameter (SD)	t Statistic (SD)	Marginal effect
Constant	1.494*10^{-4}	0	
Main street (1 if yes, 0 otherwise)	1.241	1.239	0.711
Service road (1 if yes, 0 otherwise)	1.217	1.213	0.704
Intersection (1 if yes, 0 otherwise)	1.124	1.115	0.675
Highway (1 if yes, 0 otherwise)	1.258	1.252	0.716
6:00 am – 12:00 pm (1 if yes, 0 otherwise)	-0.203*	-2.412	-0.225
12:00 pm – 6:00 pm (1 if yes, 0 otherwise)	-0.308***	-3.782	-0.361
6:00 pm – 12:00 am (1 if yes, 0 otherwise)	-0.186	-1.821	-0.204
Random Poisson Model (RPM) parameters			
Variable description	Estimated parameter (SD)	Estimated parameter (SD)	Estimated parameter (SD)
Constant	-1.053*10^{-16}	-1.053*10^{-16}	-1.053*10^{-16}
Main street (1 if yes, 0 otherwise)	1.241	1.241	1.241
Service road (1 if yes, 0 otherwise)	1.216	1.216	1.216
Intersection (1 if yes, 0 otherwise)	1.126	1.126	1.126
Highway (1 if yes, 0 otherwise)	1.259	1.259	1.259
6:00 am – 12:00 pm (1 if yes, 0 otherwise)	-0.203* (0.007)	-0.203* (0.007)	-0.203* (0.007)
12:00 pm – 6:00 pm (1 if yes, 0 otherwise)	-0.308*** (0.006)	-0.308*** (0.006)	-0.308*** (0.006)
6:00 pm – 12:00 am (1 if yes, 0 otherwise)	-0.194 (0.134)	-0.194 (0.134)	-0.194 (0.134)
* = p < 0.05, *** = p < 0.001, SD = Standard deviation			

5.3 Limitation and Future Studies

The study was carried out in three major regions in the Kingdom of Saudi Arabia; therefore, further investigations may be conducted across the whole country. Also, the study was limited due to the inadequate data acquisition form NAJM (NAJM is a company for insurance services, and a platform developed for managing activities related to crashes, working as a contractor with Saudi Traffic Sector for reporting traffic crashes and estimating the percent of their damages). In future studies, it is suggested to use information and data related to traffic police management, as there are data on all crashes in the KSA. The study was conducted for only male drivers, future studies may investigate female driver behaviour in KSA due to the current change to allow female drivers on the road, and as found in a previous study (Agbelie, 2016). NAJM has failed to monitor or even include "driving under the influence" (DUI) within any traffic-related reports. The lack of research related to this topic highlights the significance of conducting further investigations.

6. Conclusion and Recommendations

This paper studied driving behaviour in three main cities in Saudi Arabia, i.e., Makkah, Dammam and Riyadh. During the survey, 360 questionnaires were analysed. To define and measure the driving-behaviour throughout these three cities, the random Poisson parameters regression model was applied. It was also used to analyse and compare the driving-behaviour, as well as to determine the significance of several factors in predicting traffic crashes. The significance of the research was to determine important factors related to road safety, which could influence legislators and key decision-makers to manage the future traffic-related need of the KSA. Two random parameters regressions were conducted for the purpose of assessing the relevance of the tested factors. These were one with driving-behaviour and LOC as the predictors and another with the time and the location of a crash as the predictors.

The results indicated that violations on the road, aggressive-behaviour, and the time of crash were significant predictors. Aggressive driving behaviour was leading to with a higher crashes number while violations on the road had a negative correlation. Also, night-time (12:00 am – 6:00 am) was shown to be another risk factor for crashes. Place of crash and locus of control were not shown as significant predictors. These results indicate possible actions that could be taken to increase the traffic safety in roads, like, improving the regulations of road-traffic at night or developing and implementing improvement programs for aggressive drivers.

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