International Journal of Engineering and Applied Sciences (IJEAS)
ISSN: 2394-3661, Volume-3, Issue-11, November 2016

Risk Factors Analysis for Drivers with Multiple Crashes

Mohamed Shawky, Abdulla Al-Ghafli

Abstract— **Identifying the drivers who frequently involvement in traffic crashes (i.e. high-risk drivers) is the main concern of all road safety related entities. The factors that belong to the driver's behavior are considered as leading causes of traffic crashes. Drivers' behavior can be measure based on their historical records of traffic rules violations and crashes involvements. This paper aims to investigate the characteristics of drivers who are frequently involved in severe crashes and to define the parameters that can be used to recognize the risky drivers. Historical records of about 324,644 drivers during eight years from 2008 to 2015 were analyzed. About 20 types of unsafe traffic violation types are investigated in details. The interrelationships between the at-fault drivers involved in traffic crashes during the study period and their demographic characteristics, historical records of their severe and property damage only (PDO) crashes and historical violations of total types and specific types of violations were explored.**

Negative Binomial Regression modeling approach is applied to define the associated variables that can be used to predict the driver's severe crashes involvements. The results show that females, young, local, and less driving experience drivers have higher risk to be involved in future severe crashes. In addition, the following violations can be used as predictors to define drivers with multiple crashes: exceeding speed limit by more than 50 kph, car racing involvement, alcohol use, mobile use, tailgating, entering road suddenly, not using helmet, and overtaking-related violations. The findings can also be used to develop or improve the preventative strategies against high risky drivers.

Index Terms— **Risky driving behavior, multi-crashes drivers, traffic violations, crash rate estimation. Crash-prone drivers**

I. Introduction

One of the primary missions of the traffic police in most of the world-wide countries is to enforce the drivers with aggressive attitudes and high crash risks. Each driver has a degree of risk to be involved in a crash given some factors related to the environment, human, and road. Many previous studies proved that the majority of the traffic crashes occurred due to human factors [1]. This conclusion produces a challenge to the transportation planners and decision makers to develop traffic safety strategies due to the un predictable factors of crash occurrence.

In Abu Dhabi (AD), the capital of United Arab Emirates (UAE), the driver's community is a mix of different nationality groups from all over the world where the total number of registered non-local (i.e. non-Emirati) driver groups is more than 200. Referring to the local traffic safety statistics in Abu Dhabi regarding the at-fault drivers who were involved in severe crashes (i.e. a crash with at least one injury) during the period between 2010 and 2015, about 88.5% of them are male, 40.3% aged between 18 and 30 years old, and about 35% are from Asian countries. These facts produce many challenges to Abu Dhabi government to control different backgrounds, cultures, and driving experiences of multi-national driver society. It is worth mentioning that Abu Dhabi government has a strategic target to reduce the road fatality rates from the current value of about 7.4 fatalities per 100,000 inhabitants to 3.0 fatalities per 100,000 inhabitants by year 2023. Table 1 shows the main road safety indicators in Abu Dhabi during the period from 2010 to 2015. The numbers indicate that a significant improvement in road safety has been achieved during last six years. The number of fatalities has been reduced by 34.8% and the fatality rate has been reduced by 39.8% at the end of 2015 compared to the same period in 2010.

Year	Number of severe crashes	Number of causalities	Number of serious injuries	Number of fatalities	Fatality rate per 100,000 inhabitants	Fatality rate per 10,000 registered vehicles
2010	2,537	4,307	400	376	12.3	5.4
2011	2,283	3,871	390	334	10.7	4.3
2012	2,056	3,498	364	271	8.7	3.3
2013	2,071	3,644	366	289	8.9	3.3
2014	1,861	3,154	240	267	7.6	2.8
2015	1,803	3,025	1478	245	7.4	2.4

Table 1: Traffic Safety main indicators in Abu Dhabi

One of the promising tools to achieve the above mentioned strategic target is to identify the high-risk drivers based on traffic safety related criteria as to be demonstrated in this study. After that, preventative programs and strategies to enforce and aware such driver group can be developed including some penalties such as license suspension, attending special road safety training courses, warning messages, etc. It is worth mentioning that no clear definition is yet published regarding "high-risk" drivers in Abu Dhabi which leaves a space for this study to set criteria to propose such definition.

Table 2 shows statistics of the traffic violations in Abu Dhabi during the period from 2010 to 2015. The table shows that the total number of violations has been increased by 130% in year 2015 compared to year 2010. This increasing trend can be justified due to the increase number of the installed automated speed enforcement devices in the last few years. The number of speed cameras has been increased from 414 in 2010 to 704

Dr. Mohmed Shawky , Assistance Professor, Department of Public works, Faculty of Engineering, Ain Shams University, Cairo, Egypt
Traffic Consultant in Traffic and Patrols Directorate, Abu Dhabi Police, Abu Dhabi, United Arab Emirates
Capt. Eng. Abudullah Al-Ghafli, Traffic and Patrols Directorate, Abu Dhabi Police, Abu Dhabi, United Arab Emirates

in 2015 (about 70.0% increment). In addition, about 198 red light violation cameras have been installed at 77 intersections during the last three years. Also, Table 2 shows that at-site enforcement (i.e., face to face traffic violation tickets) has been increased by 37% in year 2015 compared to year 2010.

Year	*Total number of violations*	*At-site violations*	*Speed-related violations*	*% of speed-related violations*	*Violation rate per registered vehicle*
2010	24,77,340	5,04,559	1,851,907	74.8%	3.5
2011	40,11,310	6,15,826	3,352,570	83.6%	5.1
2012	40,85,074	6,41,314	3,399,460	83.2%	4.9
2013	38,32,685	7,45,159	3,197,320	80.3%	4.4
2014	43,38,701	7,19,156	3,477,274	80.2%	4.6
2015	56,92,745	6,88,845	4,921,934	86.5%	6
% of change	130%	37%	165%	-	69%

Table 2: Traffic violations statistics in Abu Dhabi

On the light of previous statistical facts, the following question was raised: Was increasing the number of automated speed enforcement cameras on roads in the past years is the right approach to improve road safety levels in Abu Dhabi? In other words, Is there any relationship between the “high-risk” drivers and traffic rule violations record? This paper tries to find an answer to the mentioned question by exploring the “high-risk” drivers in terms of their historical traffic safety records (i.e. violations and crashes) in addition to their demographic characteristics. Thus, this study focuses on predicting the likelihood that a “high-risk” driver will be involved in at-fault recurrent crashes in the future using driver records from the period between 2008 and 2015 (i.e., eight years of data) that have been reported by Abu Dhabi traffic police.

II. LITERATURE REVIEW

Many researchers have attempted to determine which variables are the best predictors for traffic crashes. The examined variables in prior studies can be classified as: demographic characteristics of drivers, psychosocial (e.g., aggressiveness, impulsiveness), behavioral (e.g., crash involvements history, traffic rules violations). Early study by Peck at al. [2] concluded that the statistical nature of driver crash frequencies makes it impossible to accurately predict which individuals will or not will be involved in at-fault crashes in the future. However, many later studies found a statistically significant relationship between the number of crashes involvements and the historical number of traffic violations of the driver ([3] - [5]). The substantial body of these studies focused on establishing estimations of the potential of a driver to be involved in a crash based on prior driving records (e.g., crashes and violations).

Lui and Marchbanks [6] determined a relationship between previous traffic infractions (i.e. violations) and fatal car crashes by studying the fatal accident reporting system from 1984 to 1986 period. They suggested that the involvement in a fatal crash is not a random event and showed that the mean time between a previous traffic infraction and a fatal crash was the shortest for individuals aged 16 to 25 years, who had a mean recurrent time of 14.2 months. In addition, about 97% of the recurrent times occurred within 60 months of a given traffic infraction, with the highest risk of a fatal crash from three to seven months following the infraction.

Hauer et al. [7] examined several methods to identify drivers who are most likely to have a crash in the near future using a four-year record for a large sample of Ontario drivers. About 16 different prediction models were developed and compared. It was found that the model that made use of detailed information on age, gender, number of each of 14 types of violations, and number of at-fault crashes and not-at-fault crashes, was the most efficient model in terms of explaining the variance of estimated crash potential. The authors concluded that if the prediction model makes use of the driver’s prior crash records, the performance of the prediction model is notably improved.

The applied logistic regression approach was used by Chen et al. [8] to identify the drivers who were most likely to have one or more at-fault crash involvements, based on prior records of at-fault crash involvements drivers. The results indicated that a model that makes use of prior at-fault crash information can identify up to 23% more drivers who will have one or more at-fault crash involvements in the next two years than a model that uses violation records alone. After studying 17 logistic regression models, [9] concluded the final developed model could correctly classify crash-involved drivers up to 27.6%. In addition, the model indicated that age, gender, license class, total citations and total crashes are the greatest prediction variables of crash-prone drivers.

Alver et al. [10] explored the interaction between socio-demographic characteristics of traffic rule violators (four types of traffic violations records were aggregated) and crash history for young drivers (18-29 years old) by applying binary logit models. The results showed that 23.9% of drivers were involved in at least one traffic accident in last three years. The crash rate increases to 38.3% for drivers who received at least one traffic violation ticket in last three years and peaks to 47.4% for those who were fined for seat belt violations.

A studied targeted Kentucky drivers to develop a crash prediction model that can be used to estimate the likelihood of a driver being at fault for a near future crash occurrence by using multiple logistic regression technique. The authors dedicated that the developed model can be used to correctly classify at-fault drivers up to 74.56% with an overall efficiency of 63.34% [4]. The total number of previous at-fault crash involvements, and having previous driver license suspensions and traffic school referrals are strongly associated with a driver being responsible for a subsequent crash. In addition, a driver’s likelihood to be at fault in a crash is higher for very young or very old, males, drivers with both speeding and non-speeding citations, and drivers that had a recent crash involvement.

Zhang et al. [11] analyzed crash severity and violation data of Chinese drivers. The results established the role of traffic violations as one of the major risks threatening road safety. In addition, specific risk factors associated with traffic violations and accident severity was determined. The authors suggested that to reduce traffic crashes and fatality rates, measures such as traffic regulations targeting different vehicle types/driver groups with respect to the various human, vehicle and environment risk factors are needed. Some studies proved the significant effect of specific drivers' behavior such as speeding and drunk and drug usage on the prediction of the crash-prone driver (i.e., [11] - [13]). Dissanayake [14] and Baker et al. [16] proved that the seat belt usage and alcohol usage have major effects on the crash severity. other study showed that both younger and older drivers have relatively higher speeding risk [17].

Berdoulat et al., [18], investigated the aggressiveness and impulsiveness in the prediction of risky drivers. It was found that aggressiveness and impeded progress were the best predictors of violations and aggressive violations. The results supported that transgressive driving behaviors are relevant indicators of aggressive driving. The same result was concluded by Bachoo et al. [19] from a sample of post graduate students in Durban, South Africa.

A new definition of the impulsivity in driving context was suggested by Bıcaksız and Ozkan [20] during analyzing 288 student self-reported questionnaires in driving behavior, violations and accident involvements. Machado-Leon et al. [21] investigated crash risk perceptions in an inter-city, two-way road context of 492 drivers by using a Stated Preference ranking survey. The study that all risky driving behaviors showed a significant potential effect on crash risk perceptions, and model's results allowed to differentiate more important from less important unsafe driving behaviors based on their weight on perceived crash risk.

III. DATA PREPARATION AND ANALYSIS METHODOLOGY

A. Database Preparation and Sample Size Selection

The employed data in this study were extracted from four different datasets of Abu-Dhabi traffic police during the period from 2008 to 2015. These datasets are: 1) traffic violation system, 2) property damage only (PDO) crashes system, and 3) severe crashes system, and 4) licensed drivers' system. Individual drivers' data were integrated in one comprehensive database by using the driver's unique traffic code that is given to each licensed driver at the day when he/she issued a driving license.

The total number of registered driving licenses in year 2008 was 636,907 and increased to 1,234,009 licenses by the end of year 2015. Serial processes of data filtrations were carried out to select the sample of drivers that will be used in the analysis. First, records of drivers who have private driving licenses only were used in the analysis (i.e., excluding the driving licenses of companies, governmental, diplomatic, intuitions, etc.). Second, drivers with zero records of both violations and crashes during the eight years were excluded from the analysis as well as those who do not have fully populated demographic information in the database. Finally, records of drivers who issued their driving licenses after year 2008 were not considered here to assure that all drivers in the data sample have practiced driving during the analysis period.

Accordingly, the data sample was reduced to be 324,644 drivers. The drivers existed in the data sample recorded a total number of 4,116,149 traffic violations; 578,619 property damage only (PDO) crashes (i.e. any crash without any injury or fatality); and 7,676 severe crashes (i.e., any crash with at least one injury or fatality). The database is structured to show the detailed historical records of each individual driver as well as groups of selected traffic violation types that have direct or indirect impact on road safety, at-fault crash involvements and demographic characteristics. These violations have been clustered into 20 groups of violations by aggregating some types in one group, for instance, the (overtaking-related violations) group which includes four types of violation: overtaking from the right, overtaking in prohibited locations, overtaking from shoulder, dangerous overtaking behavior.

B. Data Analysis Methodology

To achieve the objectives of this paper, the analysis process was conducted in two stages:

1) The first stage aims to develop the relationships between the severe crash rates per drivers in terms of violations types, drivers' demographic characteristics and the frequency of the violation types and crashes per drivers. In this stage the violations type and drivers' characteristics that have high severe crash rates can be recognized.
2) The second stage provides an estimation model to determine the best predictors/variables that can be used to identify "high-risk" drivers (i.e., the drivers have a highest likelihood to be involved in crashes in the future) using negative binomial regression model.

IV. DATA ANALYSIS

A. Interrelationship between Crash Rates and Violation Records of Drivers

Unlike traffic crashes, not all traffic violation types are indicative of risky driver's behavior or are predictors to future crashes such as: "illegal parking, driving with expired license, etc." Therefore, in the primary analysis of this study, the driver's violations were classified into two classes. Class (I): speed-related violations which includes six types of violations. Class (II): risky behavioral violations which includes 14 types of unsafe behavior violations such as: tailgating, mobile use when driving, non-seatbelt use, sudden lane changing, etc. Accordingly, drivers were classified into different groups based on their historical records of violation's type.

Crash rates and percentage of drivers involved in crashes of each group of drivers as shown in Table 3. It shows that drivers of class II have higher rates of severe crashes than those in class I. However, class I drivers are more likely to be involved in property damage only (PDO) crashes than class II drivers. In addition, Table 3 shows that the overall severe crash rates of the studied sample of drivers is 26.1 crashes per 1,000 drivers during the data period.

Fig. 1 shows the calculated severe crash rates of drivers who belong to Class I (speeding-related violations group). This figure clearly proves the strong relationship between the speeding behavior of drivers and their crash rates as a representative of their traffic safety. The severe crash rates of the drivers are significantly increasing with higher over-speeding values exceeding the legal posted speed limit on the road. For instance, drivers who exceeded the speed limit up to 30 kph have a crash rate of 23 crashes per 1,000 drivers during the study period, however drivers who exceeded the speed limit by 60 kph have crash rates of 46 crashes per 1,000 drivers (i.e. almost double) and drivers' group of those involved in car racing on roads that have crash rates of 66 crashes per 1,000 drivers (i.e. 2.87 times more than the others).

Table 3: Crash rates and percentage of divers involved in crashes for drivers group during eight years (2008-2015)

Drivers' Group	*No. of severe crashes*	*No. of PDO crashes*	*No. of drivers*	*Drivers involved in severe crash*	*Drivers involved in PDO crash*	*Severe crash rate per 1000 driver*	*PDO crash rate per driver*	*% of drivers involved in severe crash*	*% of drivers involved in PDO crash*
All drivers	16,326	965,341	624,422	14,924	425,806	26.1	1.5	2.4%	68.2%
Class I	7,376	253,604	312,496	6,883	223,603	23.6	0.8	2.2%	71.6%
Class II	13,838	341,622	497,571	12,638	341,622	27.8	0.7	2.5%	68.7%

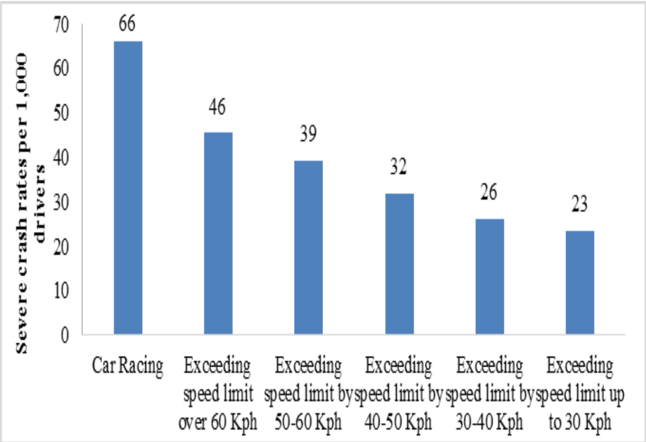


Figure 1: Severe crash rates for Class I drivers group

Fig. 2 shows the calculated severe crash rates of drivers who belong to Class II violations group. It shows that alcohol usage drivers have the highest crash rates (i.e. about 4.8 times more than the average rate of all drivers shown in Table 3). On the other hand, crash rates of drivers using mobile phones while driving has a relative lower crash rate. This result is not an accurate representation of its severity level; this is because such violations are difficult to be cited by the traffic police specially on the highways where most of sever crashes occur which leave a relative lower citation records in the violation database that is reflected in lower crash rate.

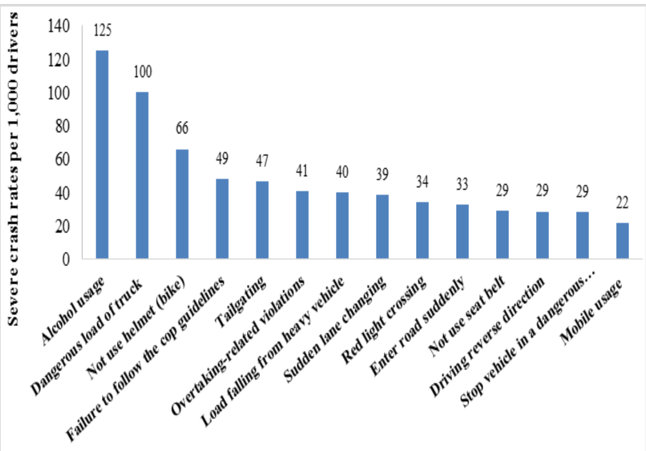
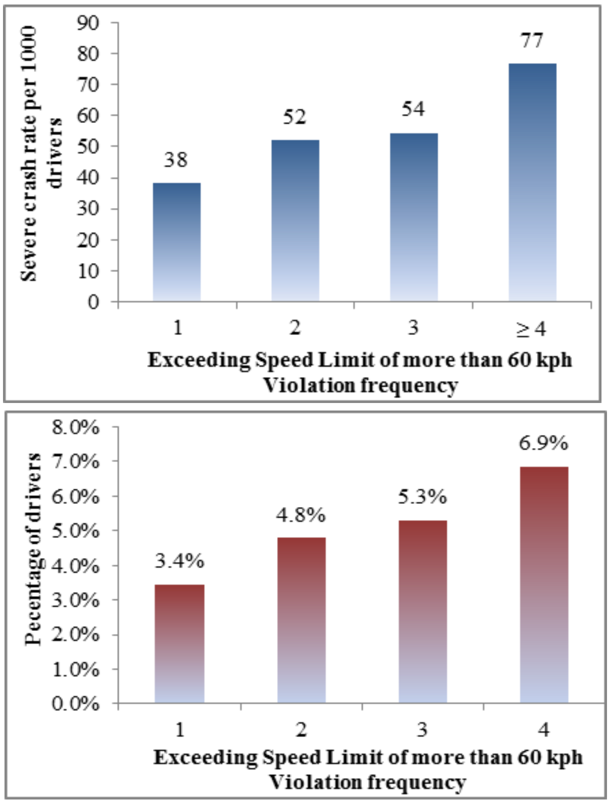


Figure 2: Severe crash rates for Class II drivers group

C. Frequency of Violations Impact and Crashes per Driver

The frequency of the violation (i.e., number of repeating the same violation type) by the individual drivers was investigated for all type of violations during the study period. Due to the size limitation of this paper, an example of these analyses is presented. Fig. 3-a and 3-b show an example of the analysis outcomes for the violation titled "Exceeding the speed limit of more than 60 kph". These figures show a significant increase of crash rates and percentages of drivers involved in severe crashes by increasing the frequency of the violation numbers. Drivers who get four or more violation tickets of this violation have about double crash rates compared to drivers who get only one ticket.



(a) With severe crash rate

(b) With percentage of drivers

Figure 3: Crash rates and percentage of drivers with respect to the frequency of the violation (Violation example: Exceeding speed limit by more than 60 kph)

ISSN: 2394-3661, Volume-3, Issue-11, November 2016

Fig. 4 shows the crash rates of the driver's group based on their records number of all types of violations. in general, this figure shows that the crash rate of drivers increases with increasing the total number of traffic violations of individual drivers.

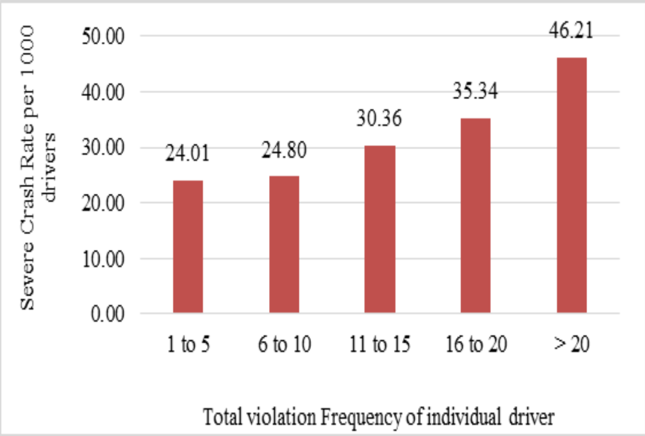


Figure 4: crash rates based on total number of violations of the driver

Fig. 5 shows the relationship between the frequency of severe crashes of individual drivers and PDO crashes records. This figure shows that drivers have more than one severe crashes were involved in higher PDO crash rates which means the PDO crashes records of the drivers can be used as indictor for the potential of the driver to be involved in severe crashes.

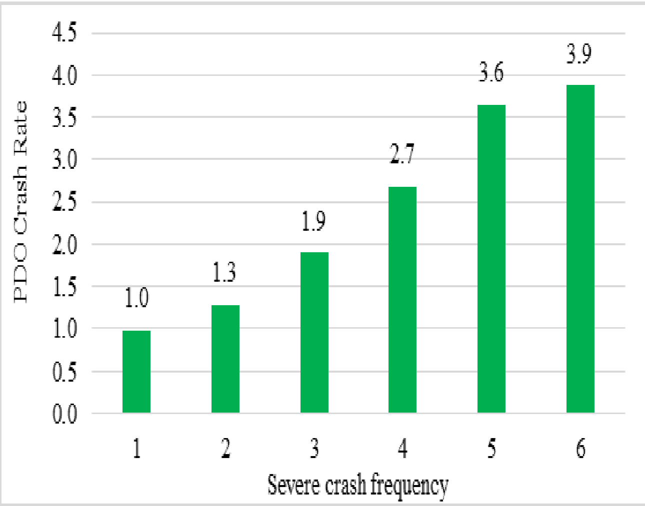


Figure 5: Frequency of severe crashes of drivers and PDO crashes records

D.Drivers' Demographic Characteristics Impact

The calculated crash rate for male drivers is almost very close to that for female (about 26.2 severe crashes per 1,000 drivers). Considering the driver's age group, Fig. 6 shows the crash rates of different age groups of Abu Dhabi registered drivers. It shows higher crash rates for very young and very old drivers. This conclusion is supported with the driving experience of the driver where the mid aged drivers (i.e. with higher driving experience) have relatively lower crash rates since they became familiar with the road circumstances and hence drive more safe. However, the older drivers (i.e. drivers with age group of 65 years old and more) lose their perception/ reaction characteristics which make them more involved in sudden crashes.

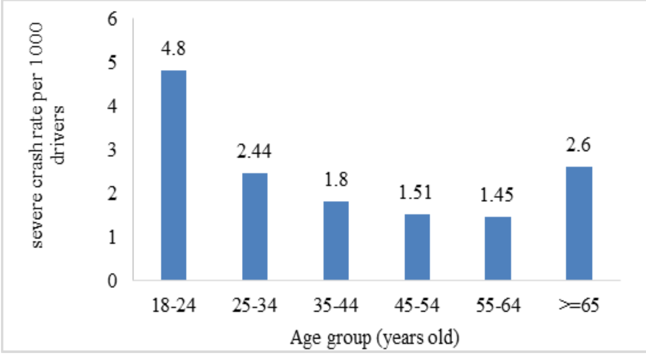
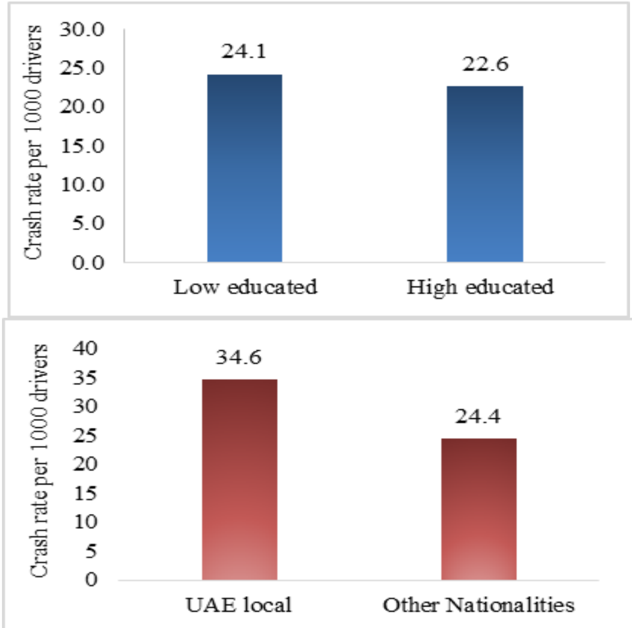


Figure 6: Crash rate of the driver's age group

Educational attainment of the drivers showed that the low educated drivers have higher crash rate (24.1 crashes per 1,000 drivers) of severe crashes than for the high educated ones (22.6 crashes per 1,000 drivers) as shown in Fig.7-a. In addition, local drivers showed higher crash rate (34.6 crashes per 1,000 drivers) relative to other nationalities in residing in Abu Dhabi as shown in Fig.7-b.



(a) Education level

(b) Nationality

Figure 7: Crash rate of the drivers based on education level and nationality

V. Regression Model Estimation

In this section, a regression model was developed to determine the best predictor variables that can be used to identify "high-risk" drivers in Abu Dhabi. Based on Highway Safety Manual (HSM-2010) the negative binomial regression modelling is considered as the best modeling approach to estimate the predictors variables of crash involvements [22]. There for this model were applied in this study. The negative binomial regression model form to predict the total crash frequency is shown in Equation 1:

$$Ln\ Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad (1)$$

Where, Y is the dependent variable (i.e. number of at-fault severe crashes in our case); X_1, X_2, ... X_n are the predictor variables; and β_0, β_1, β_2, ..., β_n are the regression coefficients.

Table 4: Model combinations with the investigated predictor variable groups

Model	Group variables 1 Demographic (age, gender, nationality, education, years of experience)	Group variables 2 Speeding Violations (6 types)	Group variables 3 Behavior Violations (14 types)	PDO Crashes
M1	√			
M2	√			√
M3		√		
M4		√		√
M5			√	
M6			√	√
M7	√	√	√	
M8	√	√	√	√

The SPSS statistical software package was employed to estimate the model using the customized negative binomial with log link function with the option to estimate the dispersion parameter rather than setting it to the system's default value. It accounts for the over-dispersion that is found in the crash data and quantifies an over-dispersion parameter.

Eight models with different combinations of the examined variables (predictors) were developed. Table 4 summarizes these eight models and the associate examined variables for each model. For example, it shows that the models M1, M3, and M5 used the variables croups of speeding violations, historical behavior violations, drivers' demographic characteristics, respectively. By accompanied the PDO historical records of the driver to these three groups of variables the models M2, M4 were developed.

Akaike Information Criterion (AIC) value each model which is a measure of the relative quality of statistical models are used to select the best fit model. The AIC compares different models from the same data by adjusting the -2 Log Likelihood statistic for the number of terms in the model and for the number of observations in the sample and can be calculated as follows [9].

$$AIC = -2\,Ln\,(L) + 2(K+S) \quad \text{.......................................} (2)$$

Where, L = Likelihood

K = the number od ordered values for the response variable

S = number of independent variables or covariates

Based on AIC values the best model is the model M7 which used all variables of the three groups of violation records of the drivers. One possible justification of that the PDO records of the drivers not shown in the best model is that in AD any very minor crash is consider as PDO and that represent a significant number in AD. Table 5 shows the final significant estimate parameters of the best developed model. As shown in Table 5, all the response variables are statistically significant at 95% (p-value $\leq$ 0.05).

Table 5: Results of negative binomial regression model

	Dependent variable	Regression Coefficient	Standard error	Wald χ^2	P-value	Odds ratio	Odds ratio 95% confidence limits Lower	Upper
	Intercept	-2.917	0.1030	802.672	0.000	0.054	0.044	0.066
drivers' variables	Gender	-0.290	0.0639	20.672	0.000	0.748	0.660	0.848
	Nationality	0.395	0.0513	59.232	0.000	1.484	1.342	1.641
	Age	-0.023	0.0035	41.171	0.000	0.978	0.971	0.984
	Experience	-0.024	0.0046	27.699	0.000	0.976	0.967	0.985
Violation types	Exceed peed between 50-60kph	0.030	0.0149	4.163	0.041	1.031	1.001	1.061
	Exceed speed more than 60kph	0.027	0.0134	4.070	0.044	1.027	1.001	1.055
	Reckless and running	0.124	0.0269	21.370	0.000	1.132	1.074	1.194
	Mobile use	-0.089	0.0332	7.130	0.008	0.915	0.857	0.977
	Alcohol use	1.253	0.0961	170.023	0.000	3.499	2.899	4.224
	Tailgating	0.229	0.0480	22.750	0.000	1.257	1.145	1.382
	Enter road suddenly	0.309	0.0823	14.066	.000	1.362	1.159	1.600
	Not using Helmet	0.369	0.1342	7.554	0.006	1.446	1.112	1.881
	Overtaking-related	0.094	0.0260	13.047	0.000	1.098	1.044	1.156

Regarding the drivers' demographic characteristics group, gender; nationality; age; and experience were found to be as significate predictors for estimate crash-prone drivers. Females, young, local, and low number of years' in driving experience drivers have high risk to be involved in severe crashes in the future. From the speeding violations group, exceeding speed by more than 60 kph, exceeding speed by values 50-60 kph, and reckless and running violations can be used to define the risky drivers. In addition, from the behavior violation group, the following violations were categorized to identify the risky driving behavior; alcohol use, mobile use, tailgating, entering road suddenly, not using helmet and overtaking-related violations. Accordingly, the accompanied fines and enforcement efforts should be concentrated in such violations in the future.

VI. CONCLUSION

This paper investigated the variables that predict severe crash involvement of drivers with multiple crashes in Abu Dhabi. The study conducted crash rate and frequency analyses for about 20 different drivers' groups of violations and drivers' demographic characteristics. In addition, Negative Binomial Regression modeling approach is used to define the associated variables that can be used to predict the number of severe crashes involvements. The data analysis showed strong relationships between the severe crash rates of the drivers with their historical records of POD crashes and violations. In addition, females, young, local and low number of years' in driving experience drivers have high risk to be involved in severe crashes. The model results showed that 9 violations' types are the best predictors for driver's crash involvements. these violations are: exceeding speed by more than 60 kph, exceeding speed by values 50-60 kph, reckless and running, alcohol use, mobile use, tailgating, entering road suddenly, not using helmet and overtaking-related violations.

Identifying the characteristics of drivers at increased risk of future multiple crash involvement would improve the road safety level by anticipating countermeasure actions against these drivers. To this end, massive enforcement and traffic awareness campaigns should be designed based to improve the traffic safety levels and deter the risky drivers from anticipating in future crashes or violations.

REFERENCES

[1] Karacasu, M., Er, A. (). An analysis on distribution of traffic faults in accidents, based on driver's age and gender: Eskisehir case. Procedia Social and Behavioral Science, Vol. 20, 776-785.

[2] Peck, R.C., McBride, R. S., Coppin R.S., (1971). The distribution and prediction of driver accident frequencies, Accident Analysis & Prevention, Vol. 2, pp. 243-249.

[3] Gebers, M.A., Peck, R.C., (2003). Using traffic conviction correlates to identify high accident-risk drivers. Accident Analysis and Prevention 35 (6), 903-912.

[4] Chandraratna, S., Stamatiadis, N., Stromberg, A., (2006). Crash involvement of drivers with multiple crashes. Accident Analysis and Prevention 38 (2006) 532–541

[5] Blascoa, R.D., Prietob, J. M., Cornejoa, J. M. (2003). Accident probability after accident occurrence. Safety Science 41, 481–501

[6] Lui, K.J., Marchbanks, P.A., (1990). A study of the time between previous traffic infractions and fatal automobile crashes, 1984-1986. Journal of Safety Research, Vol. 21, pp. 45-51.

[7] Hauer, E., Persaud, B. N., Smiley, A., & Duncan, D. (1991). Estimating the accident potential of an Ontario driver. Accident Analysis & Prevention, 23(2), 133-152.

[8] Chen, W., Cooper, P., Pinili, M., (1995). Driver accident risk in relation to the penalty point system in British Columbia. Accident Analysis and Prevention 26 (1), 9–18.

[9] Gerbers, A. Michael, (1999). Strategy for Estimating Drives Accident Risk in Relation to California\s Negligent-Operation Point System. Report No. CAL-DMV-RSS-99-183, California Department of Motor Vehicles, Research and Development Section.

[10] Alver, Y., Demirel, M. C., Mutlu, M.M., (2014). Interaction between Socio-demographic Characteristics: Traffic Rule Violations and Traffic Accident History for Young Drivers. Accident Analysis and Prevention, 72, 95-104.

[11] Zhang, G., Yau, K., Chen, G. (2013). Risk factors associated with traffic violations and accident severity in China. Accident Analysis and Prevention 59, 18– 25.

[12] Watson,B., Watson, A., Siskind, V., Fleiter, J., Soole, D. (2015). Profiling high-range speeding offenders: Investigating criminal history, personal characteristics, traffic offences, and crash history. Accident Analysis and Prevention 74, 87–96.

[13] Winter, J.C.F., Dodou, D., (2010). The Driver Behavior Questionnaire as a predictor of accidents: A meta-analysis. Journal of Safety Research 41 (2010) 463–470.

[14] Kim, D.H., Ramjan, L. M., Mak K. K. (2015). Prediction of vehicle crashes by drivers' characteristics and past traffic violations in Korea using a zero-inflated negative binomial model. Traffic Injury Prevention, available in http://dx.doi.org/10.1080/15389588.2015.1033689.

[15] Dissanayake, S., Lu, J. Analysis of Severity of Young Driver Accidentes: Sequential Binary Logistic Regression Modeling. Transportation Research Record, 1784, 108-114 (2002).

[16] Baker, S.P., O'Neill, B., Ginsburg, M.J., Li, G. The Injury Fact Book. Oxford University Press, New York, NY (1992).

[17] Tseng, C., (2013). Speeding violations related to a driver's social-economic demographics and the most frequent driving purpose in Taiwan\s male population. Safety Science 57, 236-242

[18] Berdoulat, E., Vavassori, D.,Mu˜noz Sastre, M. T. (2013). Driving anger, emotional and instrumental aggressiveness, and impulsiveness in the prediction of aggressive and transgressive driving. Accident Analysis and Prevention 50, 758– 767.

[19] Bachoo, S., Bhagwanjee, A., Govender, K., (2013). The influence of anger, impulsivity, sensation seeking and driver attitudes on risky driving behavior among post-graduate university students in Durban, South Africa. Accident Analysis and Prevention 55, 67– 76

[20] Bıcaksız, P., Ozkan, T., (2015). Impulsivity and driver behaviors, offences and accident involvement: A systematic review. Transportation Research Part F (2015).

[21] Machado-León, J. L., Juan de Oña , Rocío de Oña a, Eboli L., Mazzulla, G., (2016). Socio-economic and driving experience factors affecting drivers' perceptions of traffic crash risk. Transportation Research Part F 37, 41–51.

[22] Highway Safety Manual (2010), Amirian Association of State Highway and Transportation Officials (AASHTO)

Dr. Mohmed Shawky , Assistance Professor, Department of Public works, Faculty of Engineering, Ain Shams University, Cairo, Egypt, Traffic Consultant in Traffic and Patrols Directorate, Abu Dhabi Police, Abu Dhabi, United Arab Emirates

Capt. Eng. Abudullah Al-Ghafli, Traffic and Patrols Directorate, Abu Dhabi Police, Abu Dhabi, United Arab Emirates