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Investigation of Traffic Accidents Prediction Models and Effective Human Factors: A Review

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ABSTRACT

In most countries of the world, saving human lives is one of the most important and first factors that have been considered by politicians. Among the causes of death, road accident is known as one of the 10 causes of death and casualties. Therefore, paying attention to reducing the number of accidents and also reducing the severity of accidents, is the goal of the country's officials, and their planning and prioritization is in the same direction. One of the most important parts of traffic accident analysis and prediction is selecting and using appropriate models. In this study, extensive research has been tried to give a good view to researchers to choose a suitable model. Also, the human factor in accidents has been studied and the parameters affecting this factor have been studied and the most important ones have been stated. Therefore, the purpose of this study is to examine in detail the most important factors (appropriate model and appropriate parameter) in the evaluation of accidents. Results are shown that Deep learning approach/Data mining/machine learning models had the highest power with 87.27%, followed by Poisson-lognormal and generalized additive models. It was also concluded that most models were used in suburban accidents, however, there were one model “microscopic simulations” that were used more in urban accidents. Deep learning approach / Data mining / machine learning has allocated the most up-to-date research with an average close to 2016 (2015.82). Random-parameters models are next with an average of 13.4. Duration models with the lowest mean (1998.2) are at the bottom of this classification and have the oldest research. Based on this information, it can be concluded that today researchers are more inclined to new models such as Deep Learning, which may be due to the high accuracy of these models.

Keywords: Traffic Safety, Accidents Prediction Models, Human Factors, Road Safety Probability, Population

1. INTRODUCTION

The number of deaths due to traffic accidents continues to grow, reaching 1.35 million in 2016. However, the death rate has remained stable in recent years due to the world's population. The data show that progress has been made in the areas of legislation, vehicle standards and improved access to post-accident care. This progress is not fast enough to reduce the number of deaths due to population growth rates. At this rate, the Sustainable Development Goals (SDGs) will not be met until 2020 [1]. Today, many studies have been conducted on the models used to predict the number of accidents and the factors affecting them. In order to increase the information of researchers in this field, it was felt that the models used in different parts of the world should be studied and also the most important factor affecting accidents, namely the human factor, should be studied in more detail. In the following, the researches done in the field of the studied models will be reviewed.

2. TRAFFIC ACCIDENTS PREDICTION MODELS

Since crash data are discrete data, it is more appropriate to use the distribution of discrete variables such as Poisson or negative binomial to explain them [2-4]. For this modeling, if the mean and variance values of the response variable data are equal to each other, the Poisson distribution, and if the variance value is greater than the mean value (Over-dispersion), negative binomial model, suitable distribution to explain the variable response variable. Is another independent [5, 6]. If the variance of the numerical response variable is less than the mean value of this variable (Under-dispersion), special modified models (Hurdle Poisson or Negative binomial models) or generalized linear counting methods (GLM) should be used [7]. Abdel-Aty and Radwan used Poisson regression in 2000 to model the crashes, but they did not find a suitable model because of the difference between the mean and variance of the dependent variable that caused the over-dispersion. Therefore, the Poisson-gamma model or (negative binomials) was presented as an option to solve this problem. The negative binomial model has been repeatedly used in accident analysis topics on urban freeways, urban roads, and arteries [8-10]. In order to solve the problem of having a large number of zeros in crash data, the expansion of Poisson and negative binomial models has been used, which are called zero-negative binomial models [2, 8]. Innovative methods were later introduced to predict accidents to improve older models. In 2006, for example, EI-Basyouny and Sayed introduced a modified two-sentence negative technique that improved the Goodness of fit index. In [11] they implemented a negative polynomial model based on different observations at different road sections for different years. In [12] have introduced the zero-inflated negative binomial model as the best model for predicting urban highway accidents with financial loss and fatal accidents. In this study, different models such as poisson regression, negative binomial, zero inflated poisson and zero inflated negative binomial were compared. In this model, he has used variables such as the volume of the passing car by passenger car, light car and heavy car, speed, number of lanes, number of corners and number of access.

In Valorde and Juanis (2006) research, a negative binomial model has been used to model injury and fatal driving accidents based on environmental and driver characteristics, and the results of this study have shown that the negative binomial model has good performance in modeling traffic accidents [13]. Anastasopoulos and Mannering (2009) examined the accuracy of the regression model using the Poisson distribution and negative binomials and then evaluated its performance by adding a random variable to the model. The results of this study show that the negative binomial model is more accurate than the Poisson model [14]. Chang has used two models of artificial neural networks and two negative sentences in modeling freeway accidents in Taiwan, and by comparing the efficiency of the two models, he has concluded that the model of artificial neural networks is a strong alternative method for analyzing freeway accidents [15]. Shafabakhsh and Sajed (2015) modeled the prediction of the frequency of accidents in urban highway roads of Tehran. In their study, they analyzed arterial accidents in Tehran in 2005 to 2008. For this purpose, first the factors affecting the accidents of arterial passages were identified and then by examining the correlation of these factors in the occurrence of the accident, appropriate variables were constructed to develop the model of arterial accidents. Then, using numerical nonlinear regression models, they calculated a suitable model for predicting arterial accidents in Tehran. Also, in this study, they used Poisson regression models, Poisson zero-inflated regression model, negative binomial regression model, and zero-inflated negative binomial regression model, and finally compared the four constructed models, which zero-negative negative binomial regression model was chosen [16].

Due to the length of the content, the following is an attempt to provide more studies in the form of tables and figures. In which, according to the Table (1) in addition to the authors' specifications, the study area, the model used and the power of the model from the author's point of view (the author's own consent) are given.

Table 1. Crash models and their various features

Poisson model					
Advantage	**Popular in MSc students; basic model; easy to use; Suitable for situations where the average number of accidents is low**				
Disadvantage	**Weakness in over- dispersion and under- dispersion; Weakness in the low sample mean and small sample size data; The variance and the mean are equal**				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	**Researcher, Year**
84	Suburban	Jones et. al. (1991)	74	Urban	**Jovanis and Chang (1989)**
79	Urban	Miaou and Lum (1993)	72	Urban	**Joshua and Garber (1990)**
86	Suburban	Abdulhafedh, A. (2016)	82	Urban	**Miaou (1994)**
84	Suburban	Ünlü et al., (2022)	82	Urban	**Khattak et al., (2021)**
81	Suburban	Caliendo et al. (2007)	88	Suburban	**Kumar et al., (2013)**
88	Suburban	Ye et al., (2018)	86	Suburban	**Sarker et al., (2017)**
87	Urban	Kim and Lee, (2013)	86	Suburban	**Abdella et al., (2019)**
87	Suburban	Abdella et al., (2019)	88	Urban	**Khishdari and Fallah Tafti, (2017)**
Poisson gamma and Negative binomial model					
Advantage	**Easy estimation; adequate for over dispersion**				
Disadvantage	**Weakness in under-dispersion; Weakness in the low sample mean and small sample size bias**				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	**Researcher, Year**
80	Urban	Poch and Mannering (1996)	78	Urban	**Hauer et al. (1988)**
78	Urban	Maher and Summersgill (1996)	79	Urban	**Brüde and Larsson (1993)**
78	Suburban	Mountain et al. (1996)	79	Suburban	**Bonneson and McCoy (1993)**
80	Suburban	Milton and Mannering (1998)	82	Suburban	**Miaou (1994)**
78	Urban	Brüde et al. (1998)	78	Suburban	**Persaud (1994)**
77	Suburban	Mountain et al. (1998)	80	Suburban	**Kumala (1995)**
77	Suburban	Karlaftis and Tarko (1998)	79	Suburban	**Shankar et al. (1995)**
79	Suburban	Persaud and Nguyen, (1998)	76	Suburban	**Turner and Nicholson (1998)**
81	Suburban	Heydecker and Wu (2001)	79	Suburban	**Carson and Mannering (2001)**
80	Urban	Miaou and Lord (2003)	80	Suburban	**Al Haris and Arum et al. (2022)**
78	Suburban	Hirst et al. (2004)	81	Suburban	**Diaz-Corro et al. (2021)**
82	Suburban	Lord et al. (2005a)	83	Suburban	**El-Basyouny and Sayed (2006)**
86	Suburban	Lord (2006)	84	Suburban	**Kim and Washington (2006)**
83	Suburban	Lord and Bonneson (2007)	80	Suburban	**Memon, (2006)**
85	Suburban	Malyshkina and Mannering (2010b)	82	Urban	**Lord et al. (2009)**
84	Suburban	Cafiso et al. (2010a)	81	Urban	**Daniels et al. (2010)**
84	Suburban	Geedipally et al. (2012)	83	Suburban	**Lord and Geedipally, (2011)**
85	Suburban	Coruh et al., (2015)	85	Suburban	**Lord et al., (2005)**
86	Suburban	Sarker et al., (2017)	88	Urban	**Ma et al., (2017)**
83	Suburban	Kibar et al., (2013)	85	Urban	**Kamla et al., (2016)**
85	Suburban	Champahom et al., (2022)	84	Suburban	**Mohammadi et al., (2014)**
Poisson-lognormal model					
Advantage	**Useful for over-dispersion data**				
Disadvantage	**Weakness in under-dispersion; cannot estimate a varying dispersion parameter**				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	**Researcher, Year**
83	Urban	Aquero-Valverde and Jovanis (2008)	84	Suburban	**Faden et al. (2023).**
87	Suburban	Ma et al., (2008).	86	Suburban	**Lord and Miranda-Moreno (2008)**
88	Suburban	Kumar et al., (2013)	85	Urban	**El-Basyouny, K. and Sayed, T. (2009)**
88	Urban	Zhao et al., (2018)	87	Suburban	**Hosseinpour et al., (2018)**
85	Suburban	Zhan et al., (2015)	89	urban	**Wang et al., (2018)**
Zero-inflated Poisson and Zero-inflated negative binomial					
Advantage	**Predicting the occurrence of accidents on road sections (zero-crash observations)**				
Disadvantage	**It can cause theoretical inconsistencies**				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	**Researcher, Year**
79	Suburban	Shankar et al. (1997)	82	Suburban	**Miaou (1994)**
80	Suburban	Lee and Mannering (2002)	79	Suburban	**Carson and Mannering (2001)**
85	Urban	Gianluca et al. (2023)	83	Urban	**Kumara and Chin (2003)**

85	Suburban	Lord et al. (2005b)	82	Suburban	**Qin et al., (2004)**
82	Urban	Malyshkina and Mannering (2010a)	83	Suburban	**Lord et al. (2007)**
86	Suburban	Abdulhafedh, A. (2016)	85	Urban	**Šenk and Ambros , (2011)**
-	Review	Wagh and Kamalja, (2018).	83	Suburban	**Lord et al., (2005)**
85	Suburban	Kim et al., (2016)	79	Urban	**Yau et al., (2003)**
85	Suburban	Sharma, and Landge, (2013)	81	Urban	**Chin and Quddus, (2003)**
88	Urban	Khishdari and Fallah Tafti, (2017)	83	Urban	**Dong et al., (2014)**
89	Suburban	Prasetijo et al., (2020)	87	Urban	**Kim and Lee, (2013)**
88	Suburban	Champahom et al., (2023)	86	Suburban	**Guo and Sun, (2013)**
Generalized estimating equation models					
Advantage	**When data size is small, it is used to extend the size of the samples.**				
Disadvantage	**It's better to determine the type of extending sample size**				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	**Researcher, Year**
82	Suburban	Lord et al. (2005a)	86	Suburban	**Lord and Persaud (2000)**
83	Suburban	Lord and Mahlawat (2009)	84	Urban	**Wang and Abdel-Aty (2006)**
81	Suburban	Caliendo et al. (2007)	83	Suburban	**Cafiso et al. (2010)**
			84	Suburban	**Xie and Zhang (2008).**
Generalized additive models					
Advantage	**It use smooth functions of each explanatory variable and are very flexible in modeling nonlinear relationships.**				
Disadvantage	**It is difficult to implement; It is hard to be transferable to other datasets**				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	**Researcher, Year**
87	Suburban	Li et al. (2009)	86	Urban	**Khoda Bakhshi and Ahmed (2022)**
89	Suburban	Chiou et al., (2013)	88	Suburban	**Chiou and Fu, (2013)**
Random-effects models					
Advantage	**It assist in controlling for unobserved heterogeneity when the heterogeneity is constant over time and not correlated with independent variables; produce significantly lower standard errors of the crash frequency**				
Disadvantage	**It is hard to be transferable to other datasets**				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	**Researcher, Year**
80	Suburban	Shankar et al. (1998)	78	Suburban	**Johansson (1996)**
82	Suburban	Flahaut et al. (2003)	80	Urban	**Miaou and Lord (2003)**
83	Suburban	Noland and Quddus (2004)	87	Suburban	**MacNab (2004)**
82	Suburban	Li et al. (2008)	82	Suburban	**Miaou et al., (2003)**
85	Suburban	Sittikariya and Shankar (2009)	83	Suburban	**Aquero-Valverde and Jovanis (2009)**
85	Urban	Guo et al. (2010)	84	Urban	**Quddus (2008)**
86	Suburban	Chen and Tarko, (2014)	81	Suburban	**Wang et al. (2009)**
86	Suburban	Jiang et al., (2014)	88	Urban	**Ma et al., (2017)**
84	Suburban	Chin and Quddus, (2003)	87	Suburban	**Chen et al., (2016)**
86	Suburban	Pervaz et al. (2022)	86	Urban	**Lee et al., (2015)**
Negative multinomial					
Advantage	**Suitable for Repeating patterns; panel count data.**				
Disadvantage	**Weakness in under-dispersion**				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	**Researcher, Year**
81	Suburban	Hauer (2004)	82	Suburban	**Ulfarsson and Shankar (2003)**
82	Suburban	Miaou (1994)	81	Suburban	**Caliendo et al. (2007)**
80	Urban	Poch and Mannering (1996)	86	Suburban	**Geedipally et al., (2012).**
Random-parameters models					
Advantage	**allow the coefficients of predictors to vary across the countries/regions per an analyst-specified continuous distribution; perform well in describing the parameter heterogeneity**				
Disadvantage	**Complicated estimation; hard to transferable to other datasets**				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	**Researcher, Year**
84	Suburban	El-Basyouny and Sayed (2009b)	83	Suburban	**Anastasopoulos and Mannering (2009)**
85	Urban	Kamla et al., (2016)	86	Suburban	**Chen and Tarko, (2014)**
		Alrejjal et al. (2022)	88	Suburban	**Saeed et al., (2019)**
Bivariate/multivariate models					
Advantage	**Can perform different crash types simultaneously**				
Disadvantage	**Complicated estimation; it is hard to formulation of correlation matrix**				

Model Power	Study Area	Researcher, Year	Model Power	Study Area	Researcher, Year
82	Suburban	Miaou and Song (2005)	80	Urban	Miaou and Lord (2003)
84	Suburban	N'Guessan and Langrand (2005b)	83	Suburban	N'Guessan and Langrand (2005a)
83	Suburban	Song et al. (2006)	82	Suburban	Bijleveld (2005)
80	Suburban	Park and Lord (2007)	83	Suburban	Ma and Kockelman (2006)
82	Suburban	Bonneson and Pratt (2008)	82	Suburban	N'Guessan et al. (2006)
83	Urban	Ma et al. (2008)	84	Suburban	Geedipally and Lord (2009)
84	Suburban	Ye et al. (2009)	83	Urban	Depaire et al. (2008)
85	Suburban	El-Basyouny and Sayed (2009a)	83	Suburban	Aguero-Valverde and Jovanis (2009)
86	Suburban	Park et al. (2010)	84	Suburban	N'Guessan (2010)
87	Suburban	Ma et al., (2008).	83	Suburban	Kim et al. (2007)
			87	Suburban	Hosseinpour et al., (2018)
Markov switching					
Advantage	one of the most popular nonlinear time series models; useful for analyzing sources of dispersion in the data				
Disadvantage	Complicated estimation; it's hard to formulation of correlation matrix				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	Researcher, Year
83	Suburban	Park and Lord (2009)	83	Suburban	Malyshkina et al. (2009)
84	Suburban	Park et al. (2010)	83	Suburban	Malyshkina and Mannering (2010a)
			85	Suburban	Lin et al., (2013)
Duration models					
Advantage	Assessing elapsed time between crashes allows for a very in-depth analysis of data				
Disadvantage	Its force to have more detailed data than traditional crash frequency models				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	Researcher, Year
81	Suburban	Chang and Jovanis (1990)	80	Suburban	Jovanis and Chang (1989)
82	Suburban	Mayshkina and Mannering (2009)	78	Urban	Mannering (1993)
85	Suburban	Ali et al. (2019)	80	Suburban	Chung (2010)
Hierarchical/Multilevel Models					
Advantage	When data size is small, it is used to extend the size of the samples.				
Disadvantage	It's difficult to transferable to other datasets; correlation results can be difficult to interpret				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	Researcher, Year
83	Suburban	Kim et al. (2007)	84	Suburban	Jones and Jørgensen (2003)
85	Urban	Xie et al., (2013)	85	Urban	Gelman and Hill (2007)
86	Suburban	Deublein et al., (2013)	87	Urban	Xie et al., (2014)
			85	Suburban	Zhan et al., (2015)
Neural Network, Bayesian Neural Network, Bayesian and support vector machine					
Advantage	Non parametric approach does not require an assumption about distribution of data; flexible functional form; better fit; Higher analysis speed				
Disadvantage	Complicated estimation process; may not be transferable to other datasets; The type of variables and operators may not be specified.				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	Researcher, Year
82	Suburban	Chang (2005)	89	Suburban	Singh et al. (2020)
85	Suburban	Xie et al. (2007)	88	Urban	Wicaksana et al. (2021)
86	Suburban	Abdulhafedh, A. (2016)	83	Suburban	Li et al. (2008)
82	Urban	Akgüngör and Dog˘an (2009)	85	Suburban	Li et al. (2009)
83	Suburban	Li and Zhao (2002)	86	Suburban	Çodur and Tortum (2015)
83	Suburban	Akgüngör and Dog˘an, (2009)	85	Suburban	Li-yan et al. (2010)
82	Suburban	Zhang et al. (2011, August).	86	Suburban	Fu and Zhou (2011, August).
83	Suburban	Li et al., (2009)	88	Suburban	Yasin Çodur and Tortum, A. (2015)
85	Suburban	Wenqi et al., (2017)	89	Suburban	Huang et al.,(2016)
88	Suburban	Yuan et al., (2019)	88	Suburban	Yuan et al., (2017)
88	Suburban	Olutayo and Eludire, (2014)	89	Suburban	Vlahogianni, E and Karlaftis, (2013)
89	Suburban	Yasin Çodur and Tortum (2015)	86	Urban	Basso et al., (2018)
88	Urban	Khishdari and Fallah Tafti (2017)	87	Suburban	Pettet et al., (2017)
microscopic simulation					
Advantage	Easy to simulate; Level of risk can be assessed;				

Disadvantage	Micro-simulation packages have not been specifically developed for safety analysis. Therefore, there are limitations when analyzing the dynamic behavior of traffic for conflict evaluation. Only limited types of conflicts can be described using surrogate safety indicators.				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	**Researcher, Year**
87	Urban	Ahmed et al. (2021)	82	Urban	**Barceló et al. (1994)**
83	Urban	Cunto and Saccomanno (2008)	82	Urban	**Cunto and Saccomanno (2007)**
84	Urban	Saccomanno et al. (2008)	81	Suburban	**Cheol and Taejin (2010)**
84	Suburban	Yang et al. (2010)			
Fuzzy Logic/Neuro Fuzzy					
Advantage	**Can dramatically reduce uncertainty in comparison with the classic binary state so that determiner managers can reduce uncertainty of the domain by identifying different accident scenarios more effectively and can more successfully reduce accidents and prevent their future outcomes by means of output values of the model as fuzzy model forecasting.**				
Disadvantage	**Complicated implementation**				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	**Researcher, Year**
84	Suburban	Wang et al. (2011)	84	Urban	**Meng, et al. (2009)**
			85	Suburban	**Hosseinpour et al., (2013)**
Deep learning approach/Data mining/machine learning					
Advantage	**can better account for heterogeneity issues in traffic crash prediction; could be applied to other roadway networks; more accuracy**				
Disadvantage	**To get accurate results, a lot of data is needed; There is a need for up-to-date and powerful computer systems.**				
Model Power	Study Area	Researcher, Year	Model Power	Study Area	**Researcher, Year**
85	Suburban	Zargari and Rad (2023)	87	Suburban	**Yuan et al. (2018, July)**
86	Suburban	Li et al., (2016)	84	Urban	**Chen et al. (2016, February)**
88	Urban	Liu et al., (2018)	86	Suburban	**De Oña, et al. (2013)**
89	Suburban	Zhang et al., (2018)	89	Suburban	**Park et al., (2016)**
88	Suburban	Pan et al., (2017)	89	Suburban	**Ren et al., (2017)**
87	Urban	Niyogisubizo et al. (2023)	89	Suburban	**Zhang et al., (2020)**

As shown in Figure (1), the power of the different models are compared with each other. Based on this, Deep learning approach/Data mining/machine learning models had the highest power with 87.27%, followed by Poisson-lognormal and Generalized additive models. Also, Duration model has the lowest power with 80.2%, followed by Negative binomial / Poisson gamma and Gamma models. According to Figure (1), it can be concluded that today, deep learning approach/Data mining/machine learning models can bring a bright future for safety researchers.

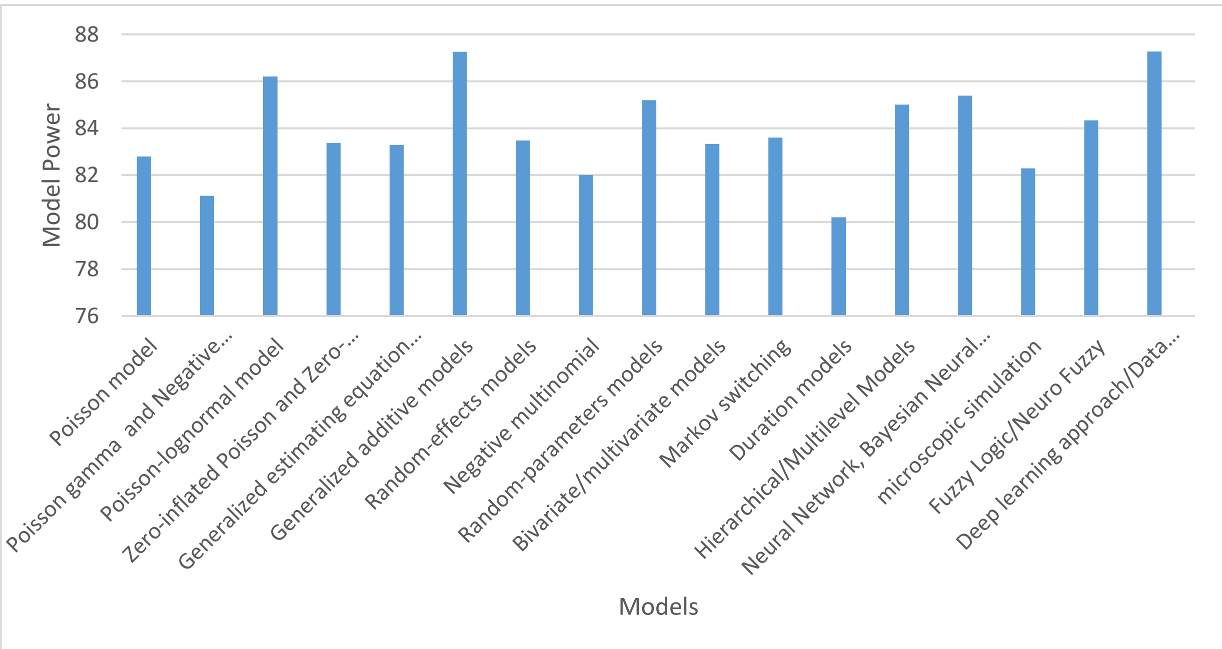

Figure 1. Different models and their power

Figure (2) shows the frequency of application of different models in accident studies related to Urban and Suburban accidents. Thus, it can be said that most models were used in suburban accidents, however, there were one model "microscopic simulations" that were used more in urban accidents. The Negative binomial / Poisson gamma model had the highest number of uses in suburban studies, followed by the Neural Network, Bayesian Neural Network models. In Urban studies, the highest number of uses of the model is related to Negative binomial / Poisson gamma and then Zero-inflated Poisson and negative binomial models and Poisson model.

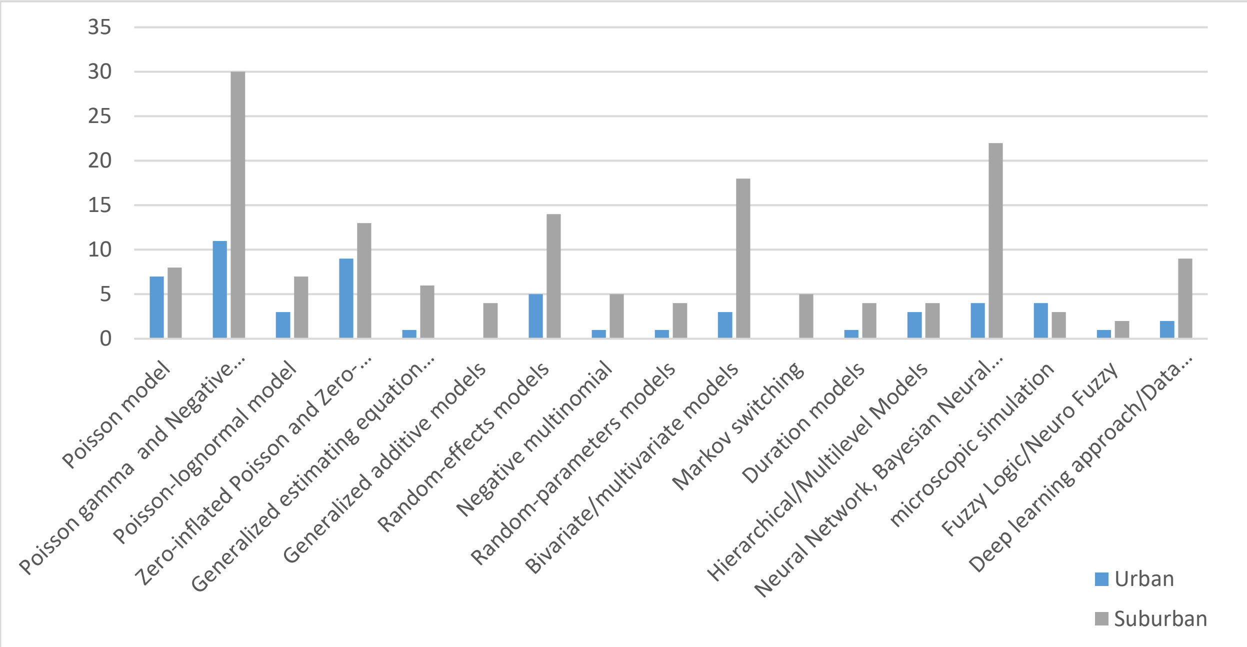

Figure 2. Frequency of application of different models in accident studies

As shown in Figure 3, the average years used by each model are shown. Thus, Deep learning approach / Data mining / machine learning has allocated the most up-to-date research with an average close to 2016 (2015.82). Random-parameters models are next with an average of 13.4. Duration models with the lowest mean (1998.2) are at the bottom of this classification and have the oldest research. Based on this information, it can be concluded that today researchers are more inclined to new models such as Deep Learning, which may be due to the high accuracy of these models.

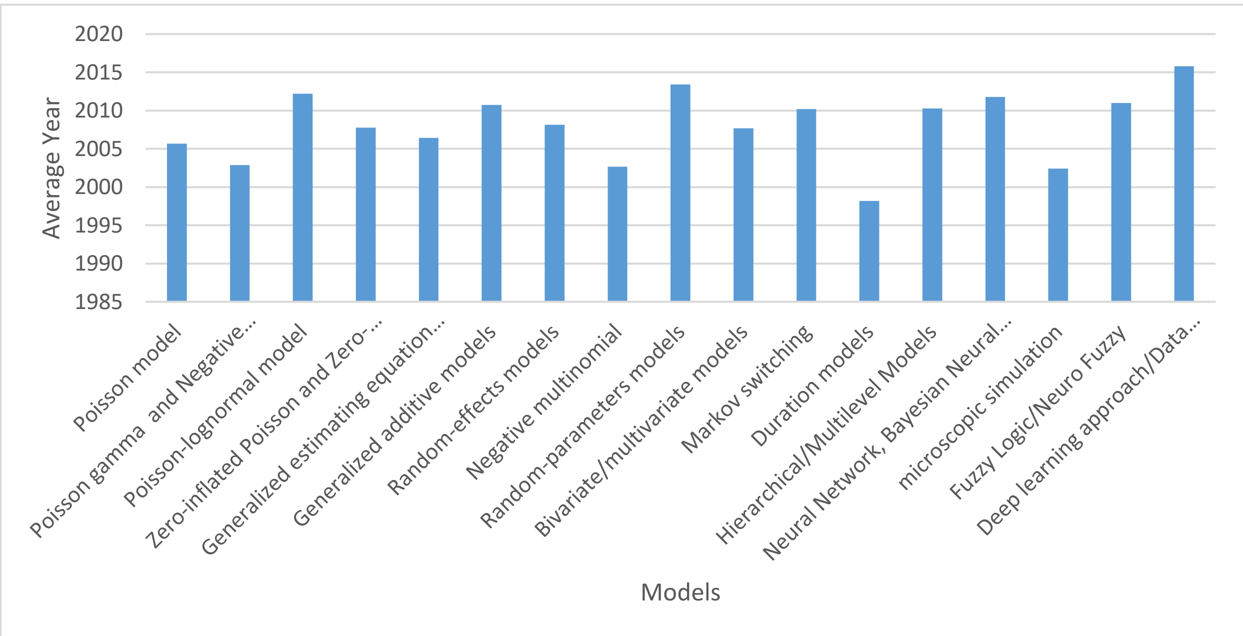

Figure 3. Average year of various researches based on the model used

When the average number of accidents on a segment of road is low, the data distribution is not normal. So the suitable model could be Poisson. This model can model discrete and rare events well. It is important to note that the Poisson distribution has only one parameter called the mean. In this model, the variance and the mean distribution are equal. In other words, the limitation of using the Poisson model is that the data distribution is equal to their mean. In various studies, the observed data indicate a high dispersion in accident data [17,18] Due to the limited Poisson distribution, this model is a bit difficult to use. Studies have shown that it is not always possible to have data that have equal variance and mean. But usually in accident frequency modeling, the variance of the data exceeds the mean of the data. In this model, scattered data play a very key role. Therefore, a negative binomial distribution is used. This distribution is a discrete distribution that offers a model for highly scattered data such as accident data. The Poisson gamma / negative binomial model is one of the most common models in crash frequency modeling. However, this model also has its limitations, in particular its weakness in scattered data reporting, and the difficulty of estimating parameter distributions is visible (when the data are small with mean sample values and small sample size) [19]. Continuing the crash models, the Poisson-lognormal model assumes that the Poisson intensity parameter in a sample of observations has a log-normal distribution. This model can have a discrete and much skewed distribution, but must be estimated numerically. Usually this model has more flexibility than Poisson's negative / gamma sentences, but it also has its limitations. One of these limitations is that model estimation is more complex because the Poisson-Lognormal distribution is not normally closed and can be affected by small sample sizes and low sample mean [20]. Another model is a generalized linear modeling method named the negative binomial zero inflated and the Poisson zero inflated model. These models were presented to explain data with a large number of zeros to be able to model areas with a large number of zero-accident segments well [21, 22]. Over-dispersion and temporal correlation are so important challenge in data when analyzing crash frequency data on roads is done. Ignoring such problems may result in under-estimation of standard errors and misleading inference for regression parameters. Therefore, appropriate methods need to get the unbiased predictions. The GEE procedure extends the generalized linear model to analysis of repeated measurements or other correlated observations [23]. Accident frequency studies have been based on generalized linear models, which a linear relationship is usually assumed between the logarithm of expected crash frequency and other independent variables. For some independent variables, such a linear assumption may be invalid. So it is worth considering other types of relationships. Generalized additive models use the smooth functions of each explanatory variable and are very flexible in modeling nonlinear relationships. Although the generalized add-on model can be more flexible than the traditional counting model, there are still limitations. Because the parameters of these models are higher, the estimation process can be very complicated precisely when the default values are not used [24]. Correlations between observations can be based on spatial considerations (data from each region may produce unobserved effects), temporal considerations (where data collected from the same observation unit over time periods can have unobserved effects) or a combination of both. To solve this problem, random effect models and fixed effect models are introduced [25]. Other models are used to model the frequency of traffic accidents, these models are used when instead of the total number of accidents, one wants to model specific models of the number of accidents (for example, the number of accidents leading to injuries, casualties, etc.). To solve this problem, bivariate / multivariate models are used because they accurately measure the correlation between the intensity levels. Markov switching models are based on that there are two unobserved safe road conditions, and road entities can move between these conditions over time. Situations are different from each other. In different situations, the frequency of accidents is caused by separate counting processes. This category can be used to assess heterogeneous populations. Markov switching models also work on the basis that a number of basic distributions generate data, and observations can change over time between these distributions [26]. Another look at the issue of accidents frequency problem is to assess the time between crashes, in contrary with the frequency of accidents over time period. The frequency of crashes and the time between crashes are clearly interdepended. In fact, count-data models point to basic distribution of time between crashes and a model of the duration of time among traffic accidents can be aggregated to generate an expected frequency in any given time period [27]. This model is used for investigating data which are characterized by correlated responses within hierarchical groups. In road traffic safety, accident data could be seen as exhibiting several levels of hierarchy. Neglecting the potential of a complex correlation structure of the data may cause to weakly estimated coefficients and standard errors, exactly when they are modeled using a traditional count-data modeling methods [28]. ANNs are algorithms that can work well for nonlinear statistical modeling. This method has many advantages such as the need for less training, high ability to identify complex nonlinear relationships between dependent and independent variables, the ability to detect all interactions between independent variables and the availability of a complete set of widely used training algorithms. But from another issue, we can point out its disadvantages, which are related to higher computational load and over fitting and the experimental nature of the development of the "black box" model in neural network systems [29]. Tease days, there are a large numbers of micro simulation software packages for different traffic parts. Studies of different simulation models with respect to general traffic modelling, as well as simulation of successor safety measure, have been undertaken. Researches has shown that many of these models may not be a viable option for safety assessment using alternative measures. Many of these models have limitations and are not commercially available. The first simulation package used for safety evaluation was PARKSIM developed by [30]. Micro-simulation packages are not specifically designed to assess safety. Therefore, there are limitations when analyzing the dynamic behavior of traffic for conflict evaluation. Only limited types of conflicts can be described using surrogate safety indicators [31]. Another model is Fuzzy Logic. This model can dramatically reduce uncertainty in comparison with the classic binary state so that determiner managers can reduce uncertainty of the domain by identifying different accident scenarios more effectively and can more successfully reduce accidents and prevent their future outcomes by means of output values of the model as fuzzy model forecasting [32]. One of the most up-to-date methods of crash data modeling is machine learning, which encompasses many aspects of today's society. Compared to conventional machine learning methods that were limited to raw data processing, deep learning method allows computational models to learn data with multiple levels of abstraction. This category can take into account the heterogeneity issues in accident prediction and can be used in other road networks without restrictions. It is more accurate, but it requires a lot of data to achieve accurate results, and it requires up-to-date and powerful computer systems [33, 34].

3. FACTORS AFFECTING ACCIDENTS

One of the most important agreed statistics on accidents and injuries is the role of 70-90% of human factors in all accidents. This has been reported in all types of transportation (land and air) [35-37]. New technologies are introduced every day in the field of road safety. Of course, their impact on human behavior and how much they reduce the risk of accidents must be examined. Efforts to understand human causes and factors help design educational interventions, new technologies, and other evaluations to have an impact on reducing the risk of an accident. Causation is a fundamental and vital goal in many systems, but it has a different meaning depending on the circumstances. In diseases and injuries, it is rarely a cause. A causal argument can be made for a factor when a change in its quality or quantity without a change in other factors changes the number or probability of injury occurring after a specified time. So this issue is often calculated using statistical methods. Numerous studies have attempted to classify the factors affecting road accidents in order to determine the causal relationship. Human (behavioral) factors seem to be the main cause in 60% of car accidents and as a factor in 97.5% of all accidents [38].

3.1 THE HUMAN FACTOR

In the culture of traffic and international definitions, the human factor includes the driver of the vehicle and pedestrians, and this factor has always played the most important role in accidents. The main factors that cause accidents caused by humans can be the driver's personal characteristics, driving violations, mental disorders, narcotics, fatigue and drowsiness, disability, inadequacy of the driver's license system, lack of necessary training to observe safety issues, lack of Manpower monitoring factors pointed out that some of the research conducted in this field is introduced below.

3.1.1 THEORETICAL APPROACHES TO THE STUDY OF HUMAN ERROR

Most early human error studies were based on psychological and behavioral theories. Psychological and behavioral theories have proven to be a good basis for theories of human error [39]. In general, both individual and systemic approaches are used to investigate human error. Most of the initial human error research of the systems was based on the error made in the first stage of the accident by the operator and emphasized the error with an individual approach and considered human error as the main cause of accidents. In recent years, to investigate human error in the road transport system, the interaction between hidden defects or hidden error conditions in the system, and errors made by the person operating the system, is often considered. For a short time, human error has been considered as a system defect instead of an individual defect [40]. Conducting human error research with a systems approach is a complex task. Although more attention has been paid to this approach, the main view of human error in the road transport system is still individual and the crimes of accidents are focused only on the driver and the role of hidden circumstances is not considered. This is undesirable for error management and safety improvement.

A. DRIVER CHARACTERISTICS

Driver characteristics are one of the most important factors in the occurrence of traffic accidents. This is so important that in many studies the human factor has been identified as influential in the occurrence of many traffic accidents.

B. LONG-TERM DRIVING

In Finland, studies were conducted on randomly selected vehicles. To conduct the above research, questionnaires containing various questions (for example, age, height, weight, driving time) that well expressed the driver's physical condition and performance in the previous three months (driving time in each shift, type of vehicle and. ..) Was prepared. Drivers were also asked about problems related to fatigue at work (number of trips during which the driver suffered from drowsiness or fear of an accident) during the last 3 months. In addition, the questionnaires asked drivers if they followed the rules for the driving time period, and also preferred to have a maximum number of hours of consecutive driving allowed. At the end of the survey, 669 drivers (34%) returned the questionnaires and responded to them [41]. Finally, by examining these questionnaires, the AHP method has been used to analyze and evaluate the effect of various factors on the problems of drowsiness. Based on the obtained results, it was found that the type of work shift and its duration are the most important parameters affecting the level of consciousness while driving. Accordingly, drivers who drive continuously for more than 17 hours are approximately 3.5 times more likely to be drowsy than those who drive only 6 hours or less.

In 2004, Lin reviewed the safety performance of motor vehicle drivers by time logistic regression. In these studies, real information about drivers was used and information about the driver was recorded every 15 minutes during the day. The driver's condition during these periods was recorded in one of three ways: "on a mission", "at rest" and "on a mission but without driving". In addition, information about the accident or not of the driver was also recorded. Finally, a number of drivers who did not crash during the test were randomly selected as a sample from among all drivers. The total number of observations in this sampling was 1934 cases, of which 694 cases were used to model the behavior of drivers with accidents and 1230 people were used to model the behavior of drivers not involved in accidents.

Using temporal logistic regression model, Lin used the parameters of driving time, experience, driving time (night or day) and a series of time-related factors to model accidents. He showed that driving time has the most direct impact on the probability of an accident. According to the results of these studies, the probability of an accident is minimal in the first 4 hours of driving, which increases by about 50% with increasing driving time to more than 4 hours, and for driving for about 7 hours, this amount reaches 80%. At the eighth and ninth hours it increases to 130% [42].

C. INSOMNIA OR DROWSINESS

One of the most important factors in heavy vehicle accidents is driver drowsiness accidents. In general, drowsiness for drivers may occur for a variety of reasons, including violations of the rules for the duration of continuous driving and night driving on consecutive days [43].

In 2000, Oron-Gilad and Shinar conducted research on Israeli military truck drivers. The reason for choosing army truck drivers was that these people have more regular work schedules than commercial vehicle drivers, and on the other hand, their activities are completely under control. In addition, profitability is not the main goal of their activity in these devices and the main criterion of greater safety is the minimum of accidents and damages [44].

For these studies, questionnaires including questions about driving and fatigue during it, information about employees, their job characteristics, sleep quality and general information about the causes of fatigue were provided to them. The above studies were performed on 314 drivers, of which 22 related information could not be used due to a large number of unanswered questions. The above studies showed that drivers who do not drive between midnight and 5 am are less likely to suffer from drowsiness.

D. THE CIRCADIAN STATE OF THE HUMAN BODY

Studies on road accident data on traffic status, age and gender of the driver show that driving at night increases the risk of accidents for young people (between 18 and 24 years old) compared to daytime driving and for older people (more than 65 years) decreases. Studies on young people in car accidents show that these accidents are 5 to 10 times more at night than driving during the day [45]. Also, regarding the relationship between people's gender and their accident hours, it was found that men are almost twice as likely as women to have an accident at the end of the day and women have almost the same trend at all hours of the day [46].

Otmani et al. used a group of 36 young and middle-aged professional drivers who had no sleep problems to simulate environmental conditions for drivers from 2 to 4 pm and 11 pm to 1 am. Half of these people drove in light traffic conditions and the other half in heavy traffic conditions [47]. During this test, the level of consciousness of the people was measured by the devices that record the brain waves of the people as well as the forms that were filled in by the driver after the end of the test period. The results of this study show that the level of consciousness of individuals according to the recorded brain scans of them and the questionnaires they filled out after driving is much lower in the afternoon than at night and the amount of drowsiness in these conditions is higher than in the morning. But there was no difference between the alertness of young and middle-aged drivers at different times of the day.

E. HUMAN FACTORS WITH REDUCED DRIVING ABILITY

Decreased ability may be short-lived, transient, or long-lasting. One of the issues is the inexperience of the driver, which is considered as a long-term ability. Driving training methods and schools have been developed accordingly and in order to eliminate this risk [48]. Although the combination of training has not been confirmed by parents and educators in some studies, temporary driving courses and step-by-step certifications can be reasonable recommendations to reduce the impact of driver inexperience on accidents [49]. Relative cognitive, motor, and sensory-perceptual deficits in the elderly predispose them to accidents, even without the presence of serious illness. Most traffic control devices are designed based on the response time to the stimulus and the "reaction time" is directly related to age. Therefore, a closer look is needed to assess the competence of older people to drive [50]. Illnesses and disabilities may affect driving ability, although well-documented studies have not confirmed this. Driver health assessors reported no difference between elderly drivers who had an accident and the control group by checking vision and routine clinical examinations. One of the most controversial issues is the "chance of an accident", which is often due to misunderstanding. There is no doubt that people like alcoholics are more likely to crash than non-alcoholics, but the question is whether crash is an inherent trait. The results of empirical research indicate that although it is possible, finding such people who are more prone to accidents by identifying their driving pattern and accidents should definitely be for medical purposes and not for offenses and legal actions. Alcoholics and drug users are seriously experiencing driving problems [51].

Consumption patterns affect short-term or long-term abilities and complex motor correction systems. People who have been arrested for drinking and driving are more likely to be involved in fatal accidents than those who have not been arrested, indicating that planning to reduce driving while consuming alcohol will be very difficult [52]. Some factors can cause a sudden drop in driving ability, including "fatigue and drowsiness." Although it is difficult to quantify this variable, drivers report a 4% chance of falling asleep. Young people have a larger share in this population. Known sleep disorders can increase the risk of drowsiness and accidents. A simple "reaction time" test can be a good predictor variable for drowsiness, and ultimately studies emphasize sleep regulation and long-term work [53]. Currently, sleep alarm devices for drivers of various abilities are being tested. Sleep disorders are one of the most common disorders and diseases in humans. Many of these disorders are directly related to age, gender, physical health status, and occupational activity. For example, sleep apnea, one of the most common sleep disorders, is exacerbated with increasing age and is more common in obese men. Important side effects of sleep disorders include daytime drowsiness, increased reaction time, decreased ability to make correct and timely decisions, and increased incidence of errors during work activities, including driving [54]. Considering the effects of sleep disorders on the occurrence of occupational accidents such as traffic accidents, by recognizing it in time, one of the most important factors in the occurrence of traffic accidents can be identified, by planning to treat and prevent driving until a significant improvement, from a significant number. Prevented traffic accidents [55]. Alcohol increases the short-term risk of accidents by removing brain inhibition, darkening judgment, and at high serum concentrations by slowing response to stimuli and slowing reflexes. Young people, women, and those with little experience with alcohol use are less likely to tolerate alcohol and more likely to have alcohol-related accidents [56]. Blood Alcohol Control In all cases of the recommended accident, individuals who regularly violate the law should be referred for follow-up and specific short-term interventions. Numerous drugs affect driving behavior by disrupting the data processing process and prolonging the response time. Amphetamines and anabolic steroids are in the first category and cause the development of dangerous behaviors. Benzodiazepines and cannabis reduce potency [57]. The rise in cocaine and marijuana use in the United States was noted because about 50 percent of drivers arrested for carelessness and not under the influence of alcohol had metabolites of these drugs in their blood. Aside from the acute effects of the drug, epidemiologists believe that long-term drug users are more likely to engage in high-risk behaviors, including driving. Concomitant use of multiple medications and the addition of alcohol has made the problem more complicated than ever [58]. Side effects of common medications such as antibiotics, cardiac glycosides, and antihistamines, as well as drug interactions, can affect driving conditions and require more careful study. Many factors have been suggested in the category of short-term capabilities, including overeating, smoking, cell phone use, and even talking to travelers.

F. HIGH-RISK BEHAVIORS

Risk-taking in the long run is equivalent to the "chance of an accident" that has behavioral roots and sometimes even cultural differences. Mediterranean people drive more dangerously than Americans. Numerous scales have been developed to predict high-risk behaviors, including adolescents, antisocial personalities, and overconfidence in their skills in studies [59]. Insight training methods for young people will raise their awareness of the limitations and give them more sensible behavior. Speed and acceleration patterns as part of driving style have affected the rate of accidents. Driving behavior not only affects the rate of accidents, which also affects the severity of accidents, such as not wearing a seatbelt, which has a protective effect of 30-46% in American studies and up to 50% in Greeks. According to studies on the distribution of injuries caused by accidents in the body, 40% of the head, 30% of the upper body, 15% of the hands and 15% of the legs are injured. Thus, the effect of using a seat belt on the restraint and safety of the head and upper body of these people will reduce by 70% of their brain, spinal cord and internal injuries. Statistics show that in 2004, the majority of deaths in the under-44 age group were due to brain and spinal cord injuries. Every year, 35,000 people in the United States die in car accidents, and if the seat belt was used, 50% of them, i.e. 17,000 people, would not perish, and the complete and correct use of the seat belt would reduce injuries by 50% and casualties by 60 to 70%. Driving in accidents. Belts should be recommended and controlled in all situations, especially for high-risk individuals, pregnant women, as well as rear passengers, although protecting children with restraints is also a must [60]. Sitting forward-leaning, often exercised by cautious or large-bodied people, increases the risk of accidents. Chances of "accident" in both long-term forms are associated with a decrease in habitual abilities and risk-taking, in the latter case in most cases alcohol and stimulant use are referred to, and in this regard methods of closely monitoring blood alcohol levels are strongly recommended. Tired, thoughtless, anxious and reckless drivers do not adapt to simple problems, sometimes even high-risk driving behavior leads to crime or suicide, unpredictable accidents are always lurking for drivers, so it is safe to use them. Episodic drugs, alcohol consumption, and their two-way relationship with the behavior of individuals have been studied, and their use can lead to seat belt failure and inefficiency of feedback mechanisms in reducing driving errors. Another approach that will be addressed here is the distribution of human error in terms of different variables [61]. Addresses new interactions of the relationship of different variables with driving hazards.

Angry drivers or those who could not control themselves were more likely to crash. With a higher number of accidents and violations, these drivers scored higher on all 5 Durkee-Buss scale hostility scales, as well as driving violence. Minor accidents were associated with more stress and violence, and higher violence and hostility were associated with driving after alcohol consumption. All violent drivers have lower education [62].

G. AGE

Young people between the ages of 18.19 and 25 are more at risk. In this age group, social deviation, driving violations, alcohol consumption and illicit drugs are reported more. Despite the fact that young people under the age of 20 have the highest rate of driving at high speeds, most of them report their speed as normal. They use less seat belts and are overconfident in their driving skills. They do not pay attention to their personal risks [63]. In general, the level of perception of the risk is low in different driving conditions. Risk factors show more personality. Driving inexperience is very common among young people, while inexperienced groups are very dangerous drivers. It takes 8 to 9 years to gain experience and stabilize driving. Elderly people have the most problems with perceptual-sensory powers, especially vision, have the highest rate of drowsiness while driving, although the rate of their accidents due to fatigue has been reported. It has also been observed that with increasing experience, the amount of sleepy driving in them has decreased [64].

H. GENDER

Men crash more and also crash harder. At the ages of 16-20 and 24-21 years, the death rate of men in accidents is twice as high as women. But after getting a driver's license, the reduction of accidents related to errors in men is doubled. Men are twice as likely as women to be involved in delinquency and aggressive driving each year. They are also three times more likely to drive after drinking alcohol. Men are less likely to wear seat belts and most angry drivers. Instead, women are more likely to crash due to impaired three-dimensional perception and positioning. Overall, their driving confidence is low [65]. In 2004, Chipman introduced a new indicator by combining two factors: travel time and distance traveled. To do this, he classified drivers with a driver's license in Ontario based on age (six age groups), gender, and region (3 regions) and compared their accident rates and death rates [66]. Based on this, Banner et al. Concluded that older drivers generally drive slower than other drivers, who have more fatal crashes than others when other conditions are stable [67].

A 2014 study by Santamariña found that men had a higher accident rate than women. According to these studies, men are more involved in injury accidents than women, while women are more involved in fatal accidents than men [68].

4. CONCLUSION

The purpose of this study is to examine in detail the most important factors (appropriate model and appropriate parameter) in the evaluation of accidents. In Table (1) in addition to the authors' specifications, the study area, the applications of models and the power of the model from the author's point of view (the author's own consent) are given. Results are shown that Deep learning approach/Data mining/machine learning models had the highest power with 87.27%, followed by Poisson-lognormal and generalized additive models. It was also concluded that most models were used in suburban accidents, however, there were one model "microscopic simulations" that were used more in urban accidents. Deep learning approach / Data mining / machine learning has allocated the most up-to-date research with an average close to 2016 (2015.82). Random-parameters models are next with an average of 13.4. Duration models with the lowest mean (1998.2) are at the bottom of this classification and have the oldest research. Based on this information, it can be concluded that today researchers are more inclined to new models such as Deep Learning, which may be due to the high accuracy of these models.

In summing up the human factors related to road traffic accidents, these factors are in two general groups: 1- Factors that depend on the process of human neurobiological development and are beyond the control and management of the driver, such as inexperience of adolescents and young drivers Cognitive abilities and skills resulting from old age. Controlling the risk posed by these factors requires restrictive regulations to ensure road safety. 2- Factors that interact in a complex way and due to the close relationship with personality traits and psychological conditions of the person can often be seen as a combination of several factors in a person that sometimes these people are a source of serious danger to themselves and others. These factors, generally classified as "high-risk driving behavior," include any behavior that increases the risk of an accident or the risk of injury following an accident (such as substance and alcohol use, speeding, overtaking, disregarding traffic signs, and warning signs). Prolonged driving without rest, not wearing a seat belt, lack of accurate inspection of the vehicle, etc.). The main basis of this type of behavior, like other daily behaviors of individuals, depends on the personality pattern and general attitudes of the individual. However, situational factors also play a role in temporarily reducing or increasing them. These people often do not have the necessary attitude and knowledge about the abnormality and high risk of their driving behavior and like other common behaviors, they justify them and even believe in these justifications. These people, if they are unusually accused, with an extravagant approach, blame people or situations for the occurrence of this behavior and always consider themselves right. Also, they often have a demanding and aggressive approach in the scene of an accident and in front of experts, and therefore punitive and control approaches do not cause a fundamental change in their long-term behavior. For this reason, any lasting change requires a change in their attitude and a belief that their behavior is risky. In traffic management, the investigating of this category requires a comprehensive approach and multi-stage plans. In the first step, assuming that individuals in society are not aware of the concepts of safe driving and the hierarchy of high-risk driving behaviors, public education and media will have an impact on attitudes and then modify behavior on a wide range of society, the effectiveness of this approach in many areas Like AIDS, the use of psychotropic substances, including driving, has been proven worldwide. In the next steps of creating a comprehensive database of drivers, especially professional drivers, in order to classify them according to the severity of high-risk driving, which can be designed and implemented according to the diversity and distribution of individuals in different groups of training programs and specific interventions. As in many areas of behavioral deviance, there will be a small number of individuals whose attitudes and behaviors will not be affected by these training programs, which in themselves will require multi-stage expert restrictive programs.

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