[Downloaded free from http://www.archtrauma.com on Wednesday, September 7, 2022, IP: 37.98.109.197]

Original Article

Identifying the Factors Affecting Occupational Accidents: An Artificial Neural Network Model

Soheil Hassanipour, Mojtaba Sepandi[1], Hadiseh Rabiei[2], Mahdi Malakoutikhah[3], Gholamhossein Pourtaghi[4]

Faculty of Health, Baqiyatallah University of Medical Sciences, [1]Exercise Physiology Research Center, Life Style Institute, Baqiyatallah University of Medical Sciences, [2]Department of Occupational Health Engineering, School of Public Health, Shahid Beheshti University of Medical Sciences, [4]Health Research Center, Life Style Institute, Baqiyatallah University of Medical Sciences, Tehran, [3]Department of Occupational Health, School of Health, Kashan University of Medical Sciences, Kashan, Iran

ORCID:

Soheil Hassanipour: 0000-0002-6661-4908
Mojtaba Sepandi: 0000-0001-6441-5887
Hadiseh Rabiei: 0000-0001-7210-4501
Mahdi Malakoutikhah: 0000-0001-9987-9286
Gholamhossein Pourtaghi: 0000-0002-9854-0536

Abstract

Background and Objectives: Occupational accidents impose high costs on organizations annually. This study aimed at investigating the factors affecting military work-related accidents using artificial neural network (ANN) and Bayesian models. **Materials and Methods:** This study was a cross-sectional survey in a military unit that examined all occupational accidents recorded during 2011–2018. First, we collected the data of the accidents using the accident database in the inspection sector of the Department of Health and the Medical Commission of the Armed Forces. ANN, Bayesian, and logistic regression models were used to analyze the data. **Results:** The results of the type of accidents showed that 219 cases of sport accidents (32.8%), 125 cases fall from height (18.7%), and 104 cases of driving accidents (15.6%) were the most common accidents. Based on the results of multivariate regression, accident variables due to fighting (odds ratio [OR] =17.21), injury to the body or back (OR = 122.55), and multiple injuries (OR = 25.72) were considered as influential and significant factors. The ANNs results showed that the highest importance factor was the injury to the body or back, multiple injuries, age, fighting, and finally, driving accident. Furthermore, the Bayesian model showed that the most important factors affecting the death consequence due to accidents were related to injuries to the body or back (OR = 276.23), multiple injuries (OR = 54.98), and accidents due to conflict (OR = 33.69). **Conclusion:** The findings show that the most important factors affecting the death consequence due to accidents in the military are the injury to the whole body, multiple injuries, age, fighting accident, and driving accident. The ANN and Bayesian models have provided more accurate information than logistic regression based on the obtained results.

Keywords: Artificial neural networks, Bayesian model, military, occupational accidents

Introduction

One of the most important effects of industrial development is the occurrence of accidents and work-related diseases.[1] Occupational accidents are one of the five leading causes of death in different age groups in the world.[2] In addition, currently, occupational accidents are the third leading cause of death globally, with about 100–120 million occupational accidents and about 200,000 deaths due to these accidents occurring worldwide each year.[3,4] According to statistics provided by the International Labor Organization, about 350,000 workers die each year due to accidents at work.[5-7]

The first step in controlling occupational accidents is to identify the causes, for which purpose, data related to accidents are

Access this article online

Quick Response Code:

Website: www.archtrauma.com

DOI: 10.4103/atr.atr_49_21

Address for correspondence: Dr. Gholamhossein Pourtaghi, PhD, Baqiyatallah University of Medical Sciences, Tehran, Iran.
E-mail: pourtaghi@bmsu.ac.ir

This is an open access journal, and articles are distributed under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 License, which allows others to remix, tweak, and build upon the work non-commercially, as long as appropriate credit is given and the new creations are licensed under the identical terms.

For reprints contact: WKHLRPMedknow_reprints@wolterskluwer.com

How to cite this article: Hassanipour S, Sepandi M, Rabiei H, Malakoutikhah M, Pourtaghi G. Identifying the factors affecting occupational accidents: An artificial neural network model. Arch Trauma Res 2021;10:195-202.

Received: 26-06-2021, **Revised:** 12-09-2021, **Accepted:** 16-09-2021, **Published:** 29-12-2021.

[Downloaded free from http://www.archtrauma.com on Wednesday, September 7, 2022, IP: 37.98.109.197]

collected at the time of its occurrence. However, studies by reviewing accident data show that most occupational accidents occurred in the middle of working hours, and amputations were the most important consequences of the accident.[8] Stricklin's study about stress in Swedish soldiers cited stress as a factor in soldiers' incidents.[9] Malliarou *et al*., in a study of occupational accidents in the Greek military, found that conscripts and professional soldiers were more likely to be injured than military officers.[10] Lazarus and Folkman also stated that one of the leading causes of traffic accidents is the inadequacy of environmental factors and the existence of stress in the drivers of military vehicles.[11]

Few studies have been conducted on the origins of military incidents in Iran; for instance, Ghaffari and Khosravi, in their research on the occurrence of military incidents in one of the provinces of Iran, founded that accidents in young groups are more than adults.[12] The results of all studies conducted in Iran indicate the weakness of the occupational safety system.

Neural networks are modern computational methods for machine learning, knowledge display, and finally, the application of knowledge gained to maximize the output responses of complex systems. Artificial neural networks (ANNs) are widely used in the medical and pharmaceutical sciences. ANNs have been commonly used in the diagnosis of cancer, cardiovascular disease, and other diseases.[13-15]

Bayesian model is one of the methods of decision support system which is a powerful tool in modeling causal relationships in the form of a network of probabilities. An essential point about the Bayesian method is that this method does not require accurate information and complete history of a fact but can also use incomplete and inaccurate information to give compelling results in estimating a system's current or future state. It also provides a consistent and flexible method for modeling uncertain situations and a graphical model based on direct perception of the interaction between different causes and effects.[16,17]

Logistic regression is used to analyze the relationship between variables, especially in the fields of medicine, psychology, and social sciences. In logistic regression, the dependent variable is a two-dimensional variable in which the effect of independent variables is shown as the role of each independent variable on the particular probability class of dependent variables.[18,19]

Logistic regression is used as a conventional method to predict health-related events. This model has limitations that, in some cases, have less predictive power. Newer techniques for prediction, such as machine learning, can significantly improve the shortcomings of the logistic regression model.[20] Neural network models were synthetic with the least assumptions under consideration variables and data structures. Hence, it can be a semi-parametric method for modeling. The advantage of obtaining closed-form posterior information is that the Bayesian logistic estimator can be obtained without using complex computational techniques. Considering that most studies in medical sciences have used the logistic regression method for prediction, the aim of this study was to compare the two new neural network and Bayesian regression methods with the logistic regression method.

The results of similar research in other countries also indicate the occurrence of military accidents. What is certain is that military employment in most countries has one of the highest risks in causing work-related accidents.[21,22] Therefore, due to the increased importance of military forces for each country, identifying the factors affecting military casualties to prevent them is particularly important. Therefore, the present study was conducted to determine the factors affecting work-related accidents in the military and provide a model using ANN and Bayesian models and compare logistic regression.

Materials and Methods

Ethical consideration

The ethics committee has approved this study of BMSU (Registration code: IR.BMSU.REC.1398.278).

Study design

This was a cross-sectional study in a military unit that examined all occupational accidents recorded from 2011 to 2018. The accidents investigated in this study were recorded in the accident database in the inspection sector, the Department of Health, and the Medical Commission of the Armed Forces. All cases were reviewed by the census, which included 668 incidents.

Relevant data were coded, and then, the incomplete information was re-examined to prepare the final form. After correcting the data and categorizing the events, the data were entered into the Excel software to be ready for data analysis.

Modeling methods

Three methods of ANNs, logistic regression, and Bayesian logistic regression were used to identify the effective factors. To do this, first, the collected data were arranged according to each plan, and then, modeling was performed. Finally, statistical analysis was performed using the SPSS version 20 (SPSS Inc., Chicago, IL, USA) and STATA version 16 (StataCorp LP, College Station, Texas). *P* value for all tests was considered <0.05.

Artificial neural networks

ANNs are used as an extension of the generalized linear model (GLM); One of the most common methods of data mining in modeling very complex and nonlinear structures. In general, each neural network consists of three types of layers: input, output, and hidden layer so that each layer consists of neurons (nodes) and synapses (links). In ANNs, some data are used as a training unit, and another category is used to test the model. Each model eventually modifies itself and provides the most accurate prediction. In ANN models, the influential variables are finally identified and weighed normally. The simplest neural network model consists of an input layer containing n predictor variables and an output layer containing

[Downloaded free from http://www.archtrauma.com on Wednesday, September 7, 2022, IP: 37.98.109.197]

only one output neuron.[23] The mentioned network calculates the following equation (Equation 1).

$$o(\mathrm{x}) = \left(\omega_o + \sum_{i=1}^{n} \omega_i x_i\right) = f(\omega_{0+} w^T \mathrm{x})$$

Where ω_0 represents the width of origin and $w = (w_1, \ldots w_n)$ represents the synaptic weights (except for the origin width). The above relation is the equation of a GLM with the link function f^{-1}, and all the calculated weights are equivalent to the parameters in the GLM. It also adds a hidden layer to the network to increase its modeling capability.[24] Hornik *et al.* have shown that any continuous fragment function can be modeled if a hidden layer exists in the neural network.[25] A neural network model with a hidden layer containing J neurons computes the following function:

$$o(\mathrm{x}) = f\left(\omega_0 + \sum_{J=1}^{I} \omega_j \,.\, f\left(\omega_{oj} + \sum_{i=1}^{n} \omega_{ij} x_i\right)\right)$$

$$= f(\omega_0 + \Sigma_{(J=1)}^{I} \omega_i . f(\omega_o j + w^T x))$$

Where ω_0 represents the width of origin of the output neuron, ω_{0j} is the width of origin of the j secret of the hidden neuron, w_j is the weight associated with the synapse that originates from the hidden neuron j and ends in the output neuron, and $w_j = (w_{1j}, \ldots, w_{nj})$ is the extraction of weights associated with synapses that terminate in the hidden neuron of *j*.

Logistic regression

In this method, which is one of the most common methods in predicting the consequences of two or more situations, first, the effective variables are identified, and after adjusting on other variables, the effect of some variables can be examined. To determine the relationship model between a dependent and an independent variable instead of a linear relationship, we need a function that varies from about 0–1. The logistic regression method uses a process called "Logistic Function." For this reason, this regression method is called logistic regression. The mentioned relationship calculates the following equation (Equation 3).

$$logit\ (p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_{1,i} + \cdots + \beta_k x_{k,i}$$

$$p = Pr\left(y_i = 1 \middle| \vec{x_i}; \vec{\beta}\right) = \frac{e^{\beta_0 + \beta_1 x_{1,i} + \cdots + \beta_k x_{k,i}}}{1 + e^{\beta_0 + \beta_1 x_{1,i} + \cdots + \beta_k x_{k,i}}} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_{1,i} + \cdots + \beta_k x_{k,i})}}$$

The advantages of the logistic regression method are it makes no assumptions about distributions of classes in feature space, it can easily extend to multiple categories (multinomial regression) and a natural probabilistic view of class predictions, good accuracy for many simple data sets, and it performs well when the dataset is linearly separable and finally is easier to implement, interpret, and very efficient to train. On the other hand, this method has limitations that can be referred to as the assumption of linearity between the dependent and independent variables; nonlinear problems can not be solved with logistic regression because it has a linear decision surface. In linear regression, independent and dependent variables are related linearly. Linearly separable data are rarely found in real-world scenarios; it is tough to obtain complex relationships using logistic regression. More powerful and compact algorithms such as neural networks can easily outperform this algorithm.

Bayesian logistic regression

This method is used as a new forecasting model and comparison with other models. In this method, the first logistic regression model is constructed based on the relationships between dependent and independent variables. Using the previous probability function, the Bayesian function is then applied based on the behavior and response of factors affecting the outcome. Building a Bayesian function has three steps, which are:

1. Determining the previous probability for the parameters
2. Determining the likelihood function for the data
3. Creating a posterior distribution function for the parameters.

If a set of training data is x and x = (x_1, x_2., x_n) are the same factors influencing the occurrence of the outcome, and also y = (y_1, y_2) is a dependent variable, the posterior probability function for samples belonging to a specific class is obtained by the following logistic function (Equation 4).

$$P(\mathrm{Class}|x_1, x_2, \cdots, x_n) = \frac{1}{1 + \exp^{\left(b + w_0 * c + \sum_{i=1}^{n} w_i * f(x_i)\right)}}$$

Doing Bayesian regression is not an algorithm but a different approach to statistical inference. The major advantage is that, by this Bayesian processing, you recover the whole range of inferential solutions, rather than a point estimate and a confidence interval as in classical regression.

Results

According to data obtained from 668 people, the injured participants' mean (standard deviation) age was 36.3 (8.9) years. Based on the final consequence in individuals, 26 deaths (3.9%) and 642 cases of disability or injuries occurred (96.1%) occurred.

Type of accident and injured limb

The results of the type of accident showed that sport accidents were 219 cases (32.8%), falls from a height of 125 cases (18.7%), and driving accidents were 104 cases (15.6%). Among the injured limbs, the most injured limbs were related to legs and hip with 280 cases (41.9%), followed by arms and hands with 173 cases (25.9%).

Job status

The job status results showed that the most accidents were

[Downloaded free from http://www.archtrauma.com on Wednesday, September 7, 2022, IP: 37.98.109.197]

fixed in military personnel with 414 cases (62%) and then in duty period with 170 cases (25.4%). Based on data analysis, conscripts were more likely to die due to accidents than the official staff, but this finding was not statistically significant (odds ratio [OR] =2.35, P = 0.271). On the other hand, military personnel did not differ in deaths due to occupational accidents compared to administrative staff (OR = 0.92, P = 0.920).

Results of artificial neural networks

Based on the ANN model, 481 samples were used for model learning and 187 samples for testing. The accuracy of the model was 97.1% in the learning phase and 96.8% in the experimental phase. Based on the results, the receiver operating characteristic for the ANN model was 0.958 [Figure 1]. Table 1 shows the ANN model performances, and also the comparison of three model performances is shown in Table 2. Figure 2 shows the neural network structure based on input variables and their effect on the outcome (death). Table 3 shows the parameter estimates of input and hidden layer.

The importance of variables

Based on the results of ANNs, the highest significance for injury to the body or back was 0.389, and the significance was 100% normalized. The significance for the other variables was as follows: for multiple injuries, the significance was 0.316 and the normalized significance was 84.1%, the age was 0.128 and the normalized significance was 33%, the accident due to the conflict was 0.107 and the normal significance was 27.5%, and finally, the accident due to driving with a significance of 0.059 and normalized significance of 15.3%. Figure 3 shows the importance of each variable in the ANN model.

Logistic regression results

Based on the results of multivariate regression, accident variables due to fighting (OR = 17.21), injury to the body or back (OR = 122.55), and multiple injuries (OR = 25.72) as effective and significant factors were identified on the outcome (death). The results of logistic regression are shown in Table 4.

Bayesian model results

Based on the variables identified from other models, the effect of age variables (<40/more than 40), driving accidents, accidents due to fighting, body or back injury, and multiple injuries on the outcome was investigated. Results of the Bayesian model are shown in Table 5. According to the results, the most important factors affecting the death consequence due to accidents were related to injuries to the body or back (OR = 276.23), multiple injuries (OR = 54.98), and accidents due to fighting (OR = 33.69). There was no significant relationship between age and driving accidents.

Discussion

This study aimed to identify the factors affecting occupational accidents in the military using ANN and Bayesian network models. The results showed that out of 668 accidents studied, 219 cases of sport accidents were the most common, and the hip and legs were the most injured limbs. Based on the ANN model, the accuracy of the model was 97.1% in the learning stage and 96.8% in the testing stage. Furthermore, the results of logistic regression showed that injury to the body or back and multiple injuries had a significant effect on the final consequence (death). Finally, based on the variables identified from other models, Bayesian logistic regression showed that the most important factors affecting the death consequence were related to injury to the body or back and multiple injuries.

Based on the results of the present study, the probability of death for accidents that occurred was 3.9%. Various studies in Iran have examined the incidence of death due to occupational accidents in civilian occupations; they showed a range from

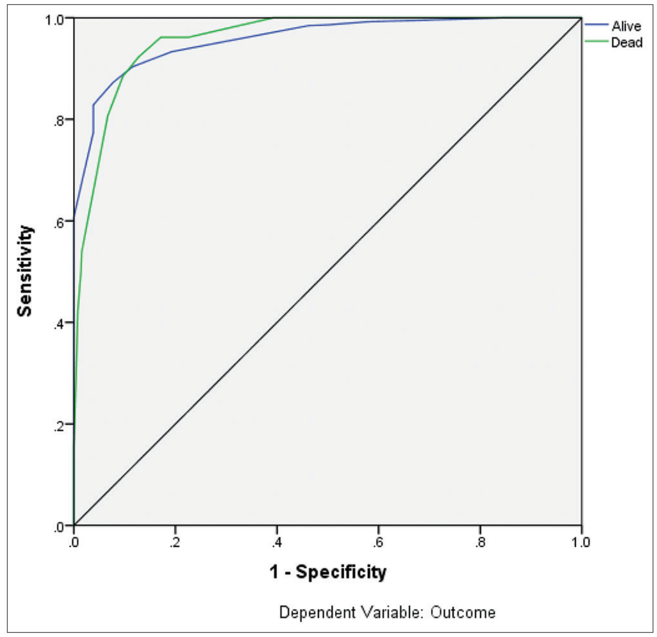

Figure 1: Receiver operating characteristic for artificial neural network model

Table 1: The artificial neural network model performances

Performance criteria	Training	Testing
R^2	0.94	0.87
MSE	0.00006	0.00002
MAPE	0.089	0.135

MSE: Mean squared error, MAPE: Mean absolute percentage error

Table 2: Comparison of three model performances

Performance indices	ANNs	BLR	LR
Accuracy rate	96.9	88.3	62.9
AUROC	0.958	0.841	0.712

ANNs: Artificial neural networks, BLR: Bayesian logistic regression, LR: Logistic regression, AUROC: Area under the receiver operating characteristic

[Downloaded free from http://www.archtrauma.com on Wednesday, September 7, 2022, IP: 37.98.109.197]

Figure 2: Structure of the neural network based on input variables and their effect on the outcome

0.4% to 1.1%.[3,8,26] This rate was 0.49% for US Air Force occupations, 0.85% for the military, 1% for the marines, and 0.67% for the Navy.[27]

The results of the present study show that the number of fatal accidents in Iranian military forces is several times higher than the number of fatal accidents in other industries in Iran as well as military centers in other countries. The reason for this can be a defect in the safety and health system of military centers or poor safety training in these centers.

The most common types of accidents in the military in the present study were sport accidents, falls from heights, and driving accidents. These results are similar to the results of the type of accidents of social security insured in Iran, which has reported the most type of accidents falling from a height and slipping,[28] Also in the study of Izadi *et al*. 59% for Collision, hit and trapping and 18.3 % for fall from a height.[8] In addition, in other studies on military forces, sport accidents, traffic accidents, and falls were the most important causes of accidents,[21] and also in Greece, the most common type of accident was related to falls from heights and moving heavy equipment.[10] The results of the studies are consistent with the present study and all of them show that occupational safety at altitude and traffic accidents are of great importance among the military.

[Downloaded free from http://www.archtrauma.com on Wednesday, September 7, 2022, IP: 37.98.109.197]

Table 3: The parameter estimates of input and hidden layer

Predictor	Predicted					
	Hidden layer				Output layer	
	H (1:1)	H (1:2)	H (1:3)	H (1:4)	Outcome (alive)	Outcome (dead)
Input layer						
Bias	0.182	0.330	-0.350	-0.585	-	-
Age (<40)	0.115	0.079	0.443	0.317	-	-
Age (>40)	0.181	0.317	-0.577	-1.01	-	-
Conflict (no)	-0.131	-0.970	0.435	-0.415	-	-
Conflict (yes)	-0.391	0.361	-0.207	0.310	-	-
Driving (no)	-0.090	-0.248	-0.389	-0.562	-	-
Driving (yes)	-0.335	0.295	0.050	0.841	-	-
Multiple trauma (no)	-0.809	-0.615	0.703	0.767	-	-
Multiple trauma (yes)	0.570	-0.354	-0.419	-0.566	-	-
Body waist (no)	0.009	-0.569	0.550	-0.735	-	-
Body waist (yes)	0.631	0.291	-0.723	0.686	-	-
Hidden layer						
Bias	-	-	-	-	0.139	-0.275
H (1:1)	-	-	-	-	-0.868	0.818
H (1:2)	-	-	-	-	-0.093	0.779
H (1:3)	-	-	-	-	0.817	-0.697
H (1:4)	-	-	-	-	-1.37	1.11

Table 4: Univariate and multivariate logistic regression results

Variable	Univariate logistic regression			Multivariate logistic regression		
	OR	95% CI	*P*	OR	95% CI	*P*
Age (<40 years vs. >40 years)	2.25	1.02-4.96	0.044	1.25	0.46-3.37	0.659
Accident during driving (yes/no)	3.04	1.32-7.03	0.009	1.57	0.55-4.47	0.393
Accident due to fighting (yes/no)	16.74	5.16-54.30	<0.001	17.21	2.68-110.28	0.003
Injury to the body or back (yes/no)	29.90	12.58-71.04	<0.001	122.55	25.29-593.71	<0.001
Multiple injuries (yes/no)	3.46	1.49-8.03	0.004	25.72	5.12-129.16	<0.001

OR: Odds ratio, CI: Confidence interval

Table 5: Results of Bayesian model

Variable	OR	SD	MCSE	Median	95% CI
Age	0.89	0.51	0.02	0.78	0.20-1.88
Accident due to fighting	33.69	53.80	2.11	19.19	1.04-107.02
Accident during driving	1.94	1.18	0.07	1.67	0.42-4.34
Injury to the body or back	276.23	374.37	18.86	174.35	18.57-793.24
Multiple injuries	54.98	18.86	3	34.26	3.26-168.08

OR: Odds ratio, CI: Confidence interval, SD: Standard deviation, MCSE: Monte carlo standard error

In the present study, conscript personnel were more likely to die due to accidents than administrative staff, but this finding was not statistically significant. Military personnel, on the other hand, did not differ much in occupational deaths compared to administrative staff. In a study of military personnel in Greece, conscripts (OR = 3.8) and professional soldiers (OR = 2.2) were significantly more affected than bureaucrats.[10] Possible reasons for this finding include a higher risk for this group of people than office workers who work in a less risky environment.

Furthermore, one of the factors influencing the outcome of age was that people under the age of 40 were more likely to die. According to a study by Malliarou *et al*. in the Greek military, there was no association between age and incidence of death.[10] On the other hand, a study by Bergman *et al*. on traffic accidents in the Scottish Army showed that people over the age of 40 were 4% more likely to die, but these findings were not statistically significant like the present study.[29] Furthermore, studies conducted in Iran show that older age is a protective factor for accidents (OR = 0.99),[26] and no significant relationship between age and death outcome in accidents has been observed.[3]

The results of the present study showed that another factor affecting death due to accidents is driving accidents. A Scottish

[Downloaded free from http://www.archtrauma.com on Wednesday, September 7, 2022, IP: 37.98.109.197]

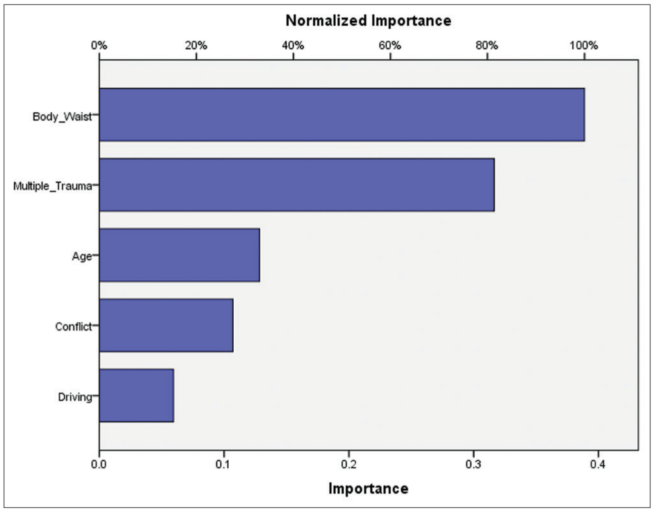

Figure 3: The importance of each variable in the artificial neural network model

military study of traffic accidents comparing soldiers (Veterans) and (nonveterans) found that Veterans were less likely to die from nonveterans in traffic accidents, but this finding was not statistically significant.[29] In addition, in a study conducted in Iran on traffic accidents, men were more likely than women, younger people were more likely than the elderly, and people with lower education were more likely to suffer fatal traffic accidents.[30,31] Possible reasons for the higher death rate in people who have a car accident, the higher severity of the accident in these situations, and noncompliance with safety tips, including not wearing a seat belt, can be mentioned.[32]

The leading causes of death in the present study were injuries to the body or back and multiple injuries, which were identified as the most important variables. A survey of multiple injuries and the resulting deaths found that people with various injuries were more likely to die.[33] In addition, a study examined the role of severity of trauma and the risk of death due to it. It showed that the resulting end would be significantly reduced if the fractures after multiple injuries are managed quickly.[34] In conclusion, compared to other studies, it can be concluded that multiple injuries are more severe, and therefore, these people are more likely to die in occupational accidents.

Finally, findings of the ANN model predicted the results of occupational accidents. In other studies, performed on trauma patients, the ANN model indicates high accuracy in predicting the outcomes associated with the patients' condition. Rughani *et al*., in their study on death prediction in trauma patients, reached 0.86 for the ANN model and 0.77 for the linear regression.[35] Shi *et al*. also concluded that ANNs had a more accurate prediction of logistic regression inhospital death (0.89 vs. 0.77).[36] Lang *et al*. reached a similar rock curve of 0.84 based on both ANN and logistic regression models in predicting death in trauma patients.[37] In general, the ANN has a stronger predictor of logistic regression[20] that one of the possible reasons may be that the neural network is not affected by the interaction between variables, but if the purpose of studying the causal relationship between variables, logistic regression can be a good choice. However, the ANNs will still have more accurate predictions, and it can be said that these two models can complement each other. In cases where the neural network cannot report individual factors, logistic regression can still provide this information.[38]

Conclusion

The present study identified the factors affecting the prevention of occupational accidents in the military using three models of ANNs, Bayesian network, and logistic regression. The results showed that the most accidents that occurred were sport accidents and falls from heights, and based on the ANN model, the model's accuracy was 97.1% in the learning phase and 96.8% in the training phase. Furthermore, the logistic regression results showed that injury to the body or back and multiple injuries had a significant effect on the outcome (death). In addition, the ANN and Bayesian models have provided more accurate information than logistic regression based on the obtained results. Therefore, the ANN method can better predict and identify the factors leading to the accident and its consequences. One of the most important limitations of the present study is the weak system of recording accident information, which causes some errors in the results. Therefore, the present study suggests that in future studies, the system of recording accident information in the military should be improved, and using other models such as system dynamics were recommended to provide more comprehensive forecasts.

Financial support and sponsorship

Nil.

Conflicts of interest

There are no conflicts of interest.

References

1. Rushton L. The global burden of occupational disease. Curr Environ Health Rep 2017;4:340-8.
2. Yadollahi M, Gholamzadeh S. Five-year forecasting deaths caused by traffic accidents in fars province of Iran. Bull Emerg Trauma 2019;7:373-80.
3. Asady H, Yaseri M, Hosseini M, Zarif-Yeganeh M, Yousefifard M, Haghshenas M, *et al.* Risk factors of fatal occupational accidents in Iran. Ann Occup Environ Med 2018;30:29.
4. Ghamari F, Mohammadfam I, Mohammadbeigi A, Ebrahimi H, Khodayari M. Determination of effective risk factors in incidence of occupational accidents in one of the large metal industries, Arak (2005-2007). Iran Occup Health 2012;9:89-96.
5. Driscoll T, Takala J, Steenland K, Corvalan C, Fingerhut M. Review of estimates of the global burden of injury and illness due to occupational exposures. Am J Ind Med 2005;48:491-502.
6. Zarocostas J. International Labour Organisation tackles work related injuries. BMJ 2005;331:656.
7. Kivimäki M, Virtanen M, Nyberg ST, Batty GD. The WHO/ILO report on long working hours and ischaemic heart disease – Conclusions are not supported by the evidence. Environ Int 2020;144:106048.
8. Izadi N, Aminian O, Esmaeili B. Occupational accidents in Iran: Risk factors and long term trend (2007-2016). J Res Health Sci 2019;19:e00448.
9. Stricklin DL. Risk assessment in international operations. Toxicol Appl

[Downloaded free from http://www.archtrauma.com on Wednesday, September 7, 2022, IP: 37.98.109.197]

Pharmacol 2008;233:107-9.
10. Malliarou M, Sourtzi P, Galanis P, Constantinidis T, Velonakis E. Occupational accidents in Greek armed forces in Evros County. BMJ Mil Health 2012;158:313-7.
11. Lazarus RS, Folkman S. Transactional theory and research on emotions and coping. Eur J Pers 1987;1:141-69.
12. Khosravi S, Ghafari M. Epidemiological study of domestic accidents in urban and rural area of Shahrekord in 1999. J Shahrekord Univ Med Sci 2003;5:53-64.
13. Paul D, Sanap G, Shenoy S, Kalyane D, Kalia K, Tekade RK. Artificial intelligence in drug discovery and development. Drug Discov Today 2021;26:80-93.
14. Ahmed FE. Artificial neural networks for diagnosis and survival prediction in colon cancer. Mol Cancer 2005;4:29.
15. Mathur P, Srivastava S, Xu X, Mehta JL. Artificial intelligence, machine learning, and cardiovascular disease. Clin Med Insights Cardiol 2020;14:1-9.
16. Carriger JF, Yee SH, Fisher WS. An introduction to Bayesian networks as assessment and decision support tools for managing coral reef ecosystem services. Ocean Coast Manag 2019;177:188-99.
17. Gelman A, Shalizi CR. Philosophy and the practice of Bayesian statistics. Br J Math Stat Psychol 2013;66:8-38.
18. Sperandei S. Understanding logistic regression analysis. Biochem Med (Zagreb) 2014;24:12-8.
19. Anderson RP, Jin R, Grunkemeier GL. Understanding logistic regression analysis in clinical reports: An introduction. Ann Thorac Surg 2003;75:753-7.
20. Hassanipour S, Ghaem H, Arab-Zozani M, Seif M, Fararouei M, Abdzadeh E, *et al.* Comparison of artificial neural network and logistic regression models for prediction of outcomes in trauma patients: A systematic review and meta-analysis. Injury 2019;50:244-50.
21. Jones BH, Perrotta DM, Canham-Chervak ML, Nee MA, Brundage JF. Injuries in the military: A review and commentary focused on prevention. Am J Prev Med 2000;18:71-84.
22. Hua W, Chen Q, Wan M, Lu J, Xiong L. The incidence of military training-related injuries in Chinese new recruits: A systematic review and meta-analysis. J R Army Med Corps 2018;164:309-13.
23. Patel JL, Goyal RK. Applications of artificial neural networks in medical science. Curr Clin Pharmacol 2007;2:217-26.
24. Jiang J, Trundle P, Ren J. Medical image analysis with artificial neural networks. Comput Med Imaging Graph 2010;34:617-31.
25. Hornik K, Stinchcombe M, White H. Multilayer feedforward networks are universal approximators. Neural Netw 1989;2:359-66.
26. Bakhtiyari M, Delpisheh A, Riahi SM, Latifi A, Zayeri F, Salehi M, *et al.* Epidemiology of occupational accidents among Iranian insured workers. Saf Sci 2012;50:1480-4.
27. Reger MA, Smolenski DJ, Skopp NA, Metzger-Abamukang MJ, Kang HK, Bullman TA, *et al.* Suicides, homicides, accidents, and undetermined deaths in the U.S. military: Comparisons to the U.S. population and by military separation status. Ann Epidemiol 2018;28:139-46.e1.
28. Bakhtiyari M, Aghaie A, Delpisheh A, Akbarpour S, Zayeri F, Soori H, *et al.* An epidemiologic survey of recorded job-related accidents by Iranian social security organization (2001-2005). J Rafsanjan Univ Med Sci 2012;11:231-46.
29. Bergman BP, Mackay DF, Pell JP. Road traffic accidents in Scottish military veterans. Accid Anal Prev 2018;113:287-91.
30. Saadat S, Soori H. Epidemiology of traffic injuries and motor vehicles utilization in the capital of Iran: A population based study. BMC Public Health 2011;11:488.
31. Hatamabadi H, Vafaee R, Hadadi M, Abdalvand A, Esnaashari H, Soori H. Epidemiologic study of road traffic injuries by road user type characteristics and road environment in Iran: A community-based approach. Traffic Inj Prev 2012;13:61-4.
32. Mokhtari AM, Samadi S, Hatami SE, Jalilian H, Khanjani N. Investigating the rate of helmet use and the related factors among motorcyclists in Kerman between 1391-92 (2012). Saf Promot Inj Prev (Tehran) 2014;2:209-14.
33. Pfeifer R, Teuben M, Andruszkow H, Barkatali BM, Pape HC. Mortality patterns in patients with multiple trauma: A systematic review of autopsy studies. PLoS One 2016;11:e0148844.
34. Bone LB, McNamara K, Shine B, Border J. Mortality in multiple trauma patients with fractures. J Trauma 1994;37:262-4.
35. Rughani AI, Dumont TM, Lu Z, Bongard J, Horgan MA, Penar PL, *et al.* Use of an artificial neural network to predict head injury outcome. J Neurosurg 2010;113:585-90.
36. Shi HY, Hwang SL, Lee KT, Lin CL. In-hospital mortality after traumatic brain injury surgery: A nationwide population-based comparison of mortality predictors used in artificial neural network and logistic regression models. J Neurosurg 2013;118:746-52.
37. Lang EW, Pitts LH, Damron SL, Rutledge R. Outcome after severe head injury: An analysis of prediction based upon comparison of neural network versus logistic regression analysis. Neurol Res 1997;19:274-80.
38. Sargent DJ. Comparison of artificial neural networks with other statistical approaches: Results from medical data sets. Cancer 2001;91:1636-42.