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Automatic Identification of Firefighters with Post-Traumatic Stress Disorder Based on Demographic Characteristics and Self-Reported Alcohol Consumption

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Abstract

Post-Traumatic Stress Disorder (PTSD) is an anxiety disorder that involves a specific set of symptoms that develop after experiencing, witnessing, or confronting an event comprising actual or threatened serious injury or death, threat or death to the physical integrity of self or others, or actual or threatened sexual violence. Firefighters participate in a wide array of stressful and traumatic events including threat of injury to self and others, death of and injuries to other people, exposure to gruesome accidents, body handling, multiple casualties, and suicides. Repeated exposure to such traumatic events places firefighters at risk for developing post-traumatic-stress (PTS) symptoms and related problems such as alcohol misuse, especially if they use alcohol as a means of coping with stress. 740 municipal firefighters completed assessments of PTS symptoms, alcohol consumption, alcohol problems, drinking motives, and coping with stress as part of a larger study. We used demographic data, data on PTS symptoms and data on alcohol related outcomes to build an automated predictor of the presence of PTSD in firefighters based on all attributes provided except those related to PTSD questionnaire. The results of the PTSD questionnaire were used to train and test the machine learning algorithms, including Neural Network (NN), Naïve Bayes Method (NB), and Decision Tree (DT), to build and validate the automated predictor for PTSD in municipal firefighters. The results of this study indicated that the automatic predictors can successfully predict PTSD with the accuracy of 88.65% using NB and 91.76% using both NN and DT. Collecting additional data points that contain more at risk individuals will improve the machine learning algorithms' prediction of at-risk individuals.

Keywords: post-traumatic stress disorder, machine learning, neural network, Naïve Bayes, decision tree, firefighters

1 Introduction

Firefighters participate in a wide array of stressful and traumatic events including threat of injury to self and others, death of and injuries to other people, exposure to gruesome accidents, body handling, multiple casualties, and suicides [15]. Moreover, they often deliver news of such tragedies to the family and friends of trauma victims [3, 15]. Firefighters in many municipalities also serve as Emergency Medical Technicians (EMTs), thereby increasing their exposure to additional traumatic events including medical emergencies, vehicle and aircraft accidents, water rescues, hazardous material incidents, search and rescue activities, and many other crises. In many urban areas, between 60-80% of 911 calls to fire departments involve medical emergencies [15].

Such exposures to traumatic events may have significant consequences. For example, the prevalence of post-traumatic stress (PTS) among firefighters is significantly higher than among general population (16-50% and 8-9%, respectively) [15, 9]. Post-Traumatic Stress Disorder (PTSD) is an anxiety disorder that involves a specific set of symptoms that develop after experiencing, witnessing, or confronting an event comprising actual or threatened serious injury or death, threat or death to the physical integrity of self or others, or actual or threatened sexual violence [1]. Individuals with PTSD frequently experience intrusion symptoms in the form of memories, nightmares,

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flashbacks, or prolonged distress. PTSD often leads to alternations in mood and cognition, and heightened arousal and stress reactivity.

Alcohol use and abuse frequently accompany experience of PTS symptoms with 52% of men and 28% of women with PTSD also meeting criteria for alcohol abuse or dependence, as compared to 25% of men and 11% of women without PTSD [11, 19]. Approximately 30% of firefighters may have problems with alcohol use, double the rate among the general population [4, 15].

Identification of individuals at risk for developing PTSD under varying traumatic circumstances has become a major public health challenge [12]. Recent studies have shown that data driven machine learning methods that can integrate large sets and many sources of information, such as biological, psychological, and social, could help identify models that provide specific forecasting for early identification of vulnerable individuals, and thus increase the opportunities for primary and secondary prevention of chronic posttraumatic stress [8, 12, 14]. Although a number of studies have been carried out to examine prospective predictors of PTSD among people recently exposed to traumatic events, most studies focused on narrow samples leaving it still unclear how well PTSD can generalize directly to other populations [14]. Studies suggest that machine learning approaches for forecasting PTSD must be extended and enriched using other data sets and adding other assumed predictors, so that accurate early prediction of individual risk can be achieved [13, 8, 14].

In summary, studies show that PTS symptoms are highly prevalent among rescue workers. Such symptoms may lead to alcohol use and abuse, particularly if such workers use maladaptive coping mechanisms or see alcohol as means of coping with stress. While several machine learning methods have been tested to identify PTSD in various populations, they do not take advantage of information specific to firefighters such as rank and longevity of service. Moreover, most of the developed methods do not take into account demographic characteristics of individuals. Thus, the purpose of our study was to build an automated predictor of PTSD in municipal firefighters while taking into consideration firefighters' rank and longevity of service as well as demographic characteristics. We used three machine learning techniques to help us identify firefighters at risk of developing PTSD in early stages and avoid potentially more serious consequences of using alcohol as coping mechanisms when dealing with PTSD. Given large amount of subjective, and therefore imprecise, data to process as well as variables whose interrelationships are unclear, we used three different machine learning algorithms – Naïve Bayes method, Neural Network, and Decision Tree – for this task since they deploy different algorithms [16, 18] in order to determine which algorithm is the most suitable for the task at hand.

2 Methods

2.1 Participants and Setting

Participants in this study were 740 uniformed firefighters from a large municipal fire department in the southwest United States, accounting for 88% of an approximate population of 844 firefighters in this municipality. Besides various demographic questions, participants completed assessments of PTS symptoms, alcohol consumption, alcohol problems, drinking motives, and coping with stress, as part of a larger study.

2.2 Measures

The following data points were collected from participants in the study:

Demographics. Demographic items included age, ethnicity, race, marital status, sex, number of years being a firefighter, rank in the fire department, and the current shift assignment.

PTSD Checklist-Civilian Version (PCL-C). The PCL-C is a 17-item instrument that assesses PTS symptoms within the past 30 days and the relationship between PTS symptoms and "stressful life experiences" [17]. Scores have a possible range of 17-85; cut off points of 44 and 50 have been recommended indicating potential PTSD [17].

Alcohol Use Disorders Identification Test (AUDIT). The AUDIT is a 10-item instrument that assesses risky alcohol consumption and screens for potential alcohol-related problems [2]. Scores range from 0 to 40 with scores of 8 or greater suggesting "at-risk drinking." The AUDIT has a reliability of $\alpha = .86$ [2].

Rutgers Alcohol Problems Index (RAPI). The RAPI is a 23-item instrument that assesses frequency of alcohol-related problems experienced within the last year [20]. Scores can range from 0-92, with higher scores suggesting greater experience of alcohol-related problems. The RAPI has a reliability of $\alpha = .92$ [20].

Daily Drinking Questionnaire (DDQ-Modified). The DDQ assesses typical consumption of alcoholic beverages by asking about drinking patterns during a "typical week" within the last month [6].

Drinking Motives Questionnaire (DMQ). The DMQ is a 20-item instrument that assesses reasons why individuals might be motivated to drink alcohol [7]. According to Cooper [7], drinking motives fall into four categories: enhancement, socialization, coping, and conformity. The DMQ-R subscales have shown adequate reliabilities (social $\alpha = .96$, coping $\alpha = .89$, enhancement $\alpha = .96$, and conformity $\alpha = .93$) [7].

Brief Cope. The Brief Cope is a 28-item instrument that assesses an individual's use of coping mechanisms within the past three months [5].

3 Results

3.1 Descriptive Analysis

Table 1 presents demographics for the study population as well as for the two scales with published cutoff criteria. As shown, the study population was predominantly male and Hispanic with the mean age of nearly 38 years. About 2/3 of firefighters were married. In terms of rank, about ¼ of firefighters were officers and ¾ were uniformed firefighters or drivers. Nearly 45% of the study population showed significant signs of PTS and nearly 33% indicated need for some kind of alcohol intervention.

Table 1: Descriptive statistics for demographics and study variables with recommended cutoff values

Variable	Mean (SD) or %
Age	37.67 (8.07)
Gender (%Male)	98.1%
Ethnicity (%Hispanic)	75.5%
Marital Status	
Single	32.6%
Married	67.4%
Rank	
Officer	27.0%
Non-Officer	73.0%
Post-Traumatic Stress (PCL-C)	27.36 (10.21)
26-35	24.7%
36-44	12.4%
>44	7.5%
Cumulative > 25	44.5%
At-Risk Drinking (AUDIT)	6.26 (5.25)
8-15 (Zone II: Simple Advice)	26.4%
16-19 (Zone III: Simple Advice + Counseling)	3.9%
20-40 (Zone IV: Refer to Specialist)	2.4%
Cumulative > 7	32.7%

Note: N = 740; Marital Status: Single includes divorced, widowed, separated, never married/single, cohabitating, or other; Rank: Officer includes Lieutenant, Captain, and Chief.

3.2 Primary Analysis

Using the information collected from 740 firefighters, we trained three machine learning algorithms (Neural Network, Naïve Bayes, and Decision Tree) to develop an automated predictor of PTSD in this study population. The input variables included the following:

- *Age* – any integer value.
- *Hispanic* – yes or no.
- *Race* – White, Black or African American, Asian, Native Hawaiian or other Pacific Islander, American Indian or Alaska Native, or other.
- *Marital status* – married, divorced, widowed, separated, single, cohabiting, or other.

- *Gender* – male or female.
- *Number of months spent in firefighter service* – any integer.
- *Rank in the firefighter department* – firefighter, driver, lieutenant, captain, or chief.
- *AUDIT questionnaire* – added values for all 10 questions in the AUDIT questionnaire (possible values 0-40).
- *RAPI questionnaire* – added values for all 23 questions in the RAPI questionnaire (possible values 0-92).
- *DDQ average weekly days.*
- *DDQ average weekly drinks.*
- *DDQ average weekly hours.*

The output consisted of two possibilities {PTSD, no PTSD}, which determines whether the person is classified to have or not to have PTSD. Since we performed supervised learning, we labeled each record as "PTSD" or "not PTSD" based on the answers to the *PTSD questionnaire*. We added answers to all 17 questions, which resulted in a score in the range 17-85. We assigned a label to each record with scores above 44 indicating the presence of PTSD [17].

All three machine learning models were trained using free software package *weka* [10]. For the Neural Network approach, we used Multilayer Perceptron with learning rate 0.1 and training time of 500. For Decision Tree approach, we used J48 tree with confidence factor of 0.5. The Naïve Bayes was trained using default values for all parameters.

To validate the accuracy of the developed machine learning algorithms, we performed 10-fold cross-validation with 90% of data points used for training and 10% of data points for testing. After combining results of all ten runs in cross-validation, the NN and DT classified correctly 91.76% of test data while NB classified correctly 88.65% of test data.

3.3 Discussion

Interestingly, neural network and decision tree developed equally good models. This is a rare coincidence to get exactly the same results by two methods, but it is very encouraging that both methods performed very well. The Naïve Bayes method performed slightly poorer than the other two methods, but still performed at a high level. A possible reason for a slightly lower performance is that the Naïve Bayes assumes independence among all input variables, which is not true in our sample. While this assumption is usually a good trade-off between accuracy and speed of execution, it might have a slight impact on final results.

Our study shows that machine learning methods can very successfully identify firefighters at risk of developing PTSD while focusing specifically on demographic characteristics of firefighters. This is a very promising result given that we used out-of-box algorithms implemented in *weka*, which are freely accessible to everyone.

3.4 Expected Improvements in Machine Learning Predictions

Even though the current machine learning methods' predictions are quite good and encouraging in supporting easy identification of firefighters susceptible to PTSD, further improvements are possible. First, a larger amount of data would allow for easier detection of patterns. Moreover, a larger amount of data would likely contain more instances of low represented classes such as the number of female individuals.

Second, the methods that we used are out-of-box algorithms provided by *weka*. A deeper modifications and parametrization of algorithms could contribute to improved results.

4 Conclusions

Due to the frequent exposure to stressful situations that firefighters experience, prevention and intervention strategies for stress-related outcomes should be a main focus for this particular population. Interventions designed to prevent or reduce PTSD symptoms due to daily exposure to disasters may also be efficient in preventing alcohol-related outcomes and decreasing alcohol consumption as a copying mechanism for stress. The fire departments may benefit from assessments and treatments of PTSD symptoms in their early stages, which would require less intense interventions, such as education and simple advice rather than counseling, diagnostic evaluation, and treatment in more severe cases when individuals with heath related problems are identified in later stages.

Firefighters often do not want to admit that they cope with PTSD, and therefore they do not willingly participate in surveys such as PCL-C to determine their level of PTSD. More likely, firefighters are willing to complete demographic and alcohol consumption surveys.

The results of this study indicated that the automatic predictors based on demographic characteristics and alcohol consumption can successfully predict PTSD among municipal firefighters with the accuracy of 88.65% using Naïve Bayes and the accuracy of 91.76% using both Neural Network and Decision Tree. Even though the results are not 100% perfect, they are highly promising and show a great potential for quick and early identification of firefighters susceptible to PTSD and potentially alcohol related problems even without their participation in PCL-C survey. Collecting additional data points that contain more at risk individuals could potentially improve the machine learning algorithms' prediction of at-risk individuals.

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