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Towards Clinical Decision Support for Veteran Mental Health Crisis Events using Tree Algorithm

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Abstract:

This research focuses on establishing a psychological treatment system especially for Milwaukee based veterans outside the traditional clinical environment of Veterans Affairs (VA). As part of this process, a 12- week intervention had been made. Data had been collected related to different health aspects and psychological measurements. With the help of expert veterans and psychologist, we had defined early warning signs, acute crisis and long-term crisis from this dataset. We had used different algorithms to predict long term crisis using acute crisis and early warning signs. At the end, we had established a clinical decision-making rule to assist peer mentor veterans to help their fellow mentee veterans especially those suffering from PTSD.

SECTION I. Introduction

Over the past decade, many US military service members have been deployed to war zones in Iraq and Afghanistan. These service members experienced different types of trauma events associated with military service. This caused them to be at the high risk of Post-Traumatic Stress Disorder (PTSD). About 15-20% of veterans suffer from PTSD and other trauma symptoms [1]. Veterans suffering from PTSD engage in different types of risky behavior like alcohol abuse, impulsivity and aggression, which may lead to interpersonal violence, suicide and unintentional injury at higher rates than civilian counterparts. Some researchers have shown that veterans suffer personal crisis events more frequently than general population [2], [3]. Because of the complex and interlocking nature of mental health crisis events, simple solutions do not work to predict and intervene rapidly in emerging crisis situations.

For the purposes of this research, we applied general crisis theory used in a variety of other domains to individual mental health crises. Crisis theory associated with major disasters and individual mental health crisis may differ on the surface, but they share some common characteristics like 1) known or unknown pre-existing system vulnerabilities [4]; 2) related early warning signs which are difficult to define against background noise [5]; 3) follow-up impacts as resources and options destroyed [6]; 4) a critical point beyond which degrees to act freely decrease significantly [7]; 5) a well-defined crisis event which requires significant external resources in order to recover or restore order [8]. Prediction of crisis events both by human or computational techniques is a very challenging task and using inaccurate prediction may lead to serious consequences [9]. This research took an initiative to quantify early warning signs, acute crisis and long-term crisis based on available information from a study on para-professional mental health intervention with US military veterans. At the end, predictive analyses had been done to forecast the occurrence of long-term crisis of veterans using early warning signs and acute crisis events.

This paper consists of five major sections. In section II, we describe the data we used for this research, section III gives a description of data analysis and preprocessing done for this research. In section IV, we discuss the models and algorithms used here, and results are discussed in section V and finally section VI concludes the paper.

SECTION II. Data

Data from 305 veterans had been collected from a community-based study which included a 12-week veteran peer mentorship program. This 12-week intervention program included three equidistant time points: intake (at the beginning of intervention), 6-week midpoint and 12-week discharge. At these three time points, different psychometric scores, including the PTSD Checklist - 5 (PCL-5), Social Adjustment Scale (SAS), specific subscales of the Deployment Risk and Resilience Inventory (DRRI-2), and the Values in Action (VIA) scale were collected. In this research, our focus was with PCL-5 score specifically. The PCL-5 is a 20-item self-assessment tool which measures the four clusters of symptoms of PTSD such as intrusion, avoidance, negative emotions and arousal. According to the Veterans Affairs Healthcare System (VA) if someone has PCL-5 over 33, he or she may be suffering from PTSD, and is considered to have a provisional diagnosis for the disorder. In between these three main time points for the study, weekly surveys were also collected where veterans were asked brief questions about their sleep quality, health, stressful experience, contacting their mentor veterans and engaging in risky behavior. Of the 305 veteran participants in this study 143 had PCL-5 above cut score (PCL-5>33). This group consists of 54 males and 246 females. Among these veterans about 87 of them are recently enrolled in school. They were involved in all branches of military (See Table I for details).

TABLE I. Participant Characteristics

Characteristics	Statistics
Gender	
Male	54
Female	246
Transgender/Missing/Unknown	5
School Enrollment	
Yes	87
No	200
Military branch	
Army	161
Navy	56
Air Force	26
Marine Corps	47
Coast Guard	2
National Guard	18
Active Duty	36
Reserve	36
Missing/Unknown	5

Military conflicts	
OEF/OIF/OND	77
Vietnam	18
Cold War	1
Central America	4
Gulf Era	22
Not Answered/Missing	187

Among these veterans a large portion of veterans were involved in the war zones of Iraq and Afghanistan. However, a major portion of them denied answering the question about military service era.

SECTION III. Prior Work

Initially, our interest was to check whether this process of treating veterans outside the traditional clinical environment is effective in reducing effects of trauma symptoms among PTSD veterans. We used repeated measures ANOVA to compare the mean PCL-5 score at intake, 6-week midpoint and 12-week discharge of this program. with a focus on PTSD symptom change using the PCL-5. We found a significant drop in mean PCL-5 score from intake to discharge. To have better understanding the effectiveness of this process we ran this test for participating veterans scoring negative for PTSD at intake (PCL-5<33) and veterans who met diagnostic cut score for PTSD (PCL-5 ≥ 33). We found that for veterans with negative PTSD score at intake, there was no significant change at discharge. However, for veterans above the diagnostic cut score of PTSD at intake, there was a significant decline in PTSD symptoms at discharge. We also tested four symptom clusters PCL-5: intrusive thoughts, avoidance, negative affect and arousal reactivity. Using repeated measures ANOVA and post-hoc tests, we compared these symptom clusters at three-time points. All symptom clusters improved from baseline to discharge except avoidance. Later on, similar analysis had been done with fixed effect model using data from more veterans. We found the same pattern of results. Overall, this preliminary work indicated that this method of community-based treatment outside the traditional clinical environment appears to be effective in reducing trauma symptoms among veterans with PTSD.. We believe that this process worked because of the personal, supportive connection between the mentors and their mentee veterans. To help understanding the behavior of PTSD veterans and to help mentor veterans to assist their mentees more effectively, our next step was to investigate ways to further empower the peer mentors with clinical decision support approaches by defining crisis events and early warning signs based on their weekly survey data and participation in this intervention. This decision support approach mirrored the practical concerns of the veteran peer mentors and our efforts to define early warning signs, acute crises, and long-term crises were driven from an implicit theory of mental health crisis events offered by the peer mentors themselves.

SECTION IV. Model and Algorithms

In this research, we have considered two algorithms to predict long term crisis in terms of acute crisis and early warning signs.

- Decision Tree: This is a decision support tool. It uses a tree like model to forecast possible consequences. It helps to identify strategy to reach a certain goal. If the outcome of interest is qualitative, then decision tree can be used for classification problem solving. On the other hand, if the outcome is quantitative, then it can be used for regression purposes. First it divides or segments the space of the predictors into several simple regions. At each region, it estimates the mean or mode of training data. This is used to predict new observation. This process of separating or segmenting the predictors space can be summarized in a tree form which is why these methods are known as decision tree methods. Generally, decision trees consist of three types of nodes: decision nodes, chance nodes, end nodes [10].
- Logistic Regression: It is a statistical model which is used to predict generally binary outcome using logistic function. It uses probability to determine the class of an object. It uses a function which gives the probability of a given object belonging to a certain class. This function is known as logistic function which is given below:

$$P(X) = \frac{e^{\beta_0+\beta_1 X}}{1+e^{\beta_0+\beta_1 X}}$$

where X represents the variable predictor and $P(X)$ represents probability of belonging to a certain class [11].

- Cross Validation: A statistical model evaluation technique. It involves several steps. At each step, it partitions the sample data into training and test set. Usually the training data set is larger than the test set. It builds the model using the training data set and evaluate it on test data set. It repeats this process until it covers all the data in training and test set. At the end it average of errors based on the number of times it repeated the process [11].

SECTION V. Results & Discussion

With the knowledge and expertise of an experienced veteran (MF) and a psychologist (ZF) and a medical anthropologist (KH), we decided to define *early warning sign* as any one weekly survey missed; an *acute crisis* as two symptoms worse for two consecutive weeks; and *long-term crisis* as the discharge survey missed (i.e complete loss to follow-up). At the beginning, we considered the participation of veterans and their symptoms change within the first three weeks of their entry into this intervention. Each week participation is considered as binary variable, ie., whether a given week, they had missed or not. Similarly, symptom change information was considered as a binary variable such that any two weekly symptoms worse in two consecutive weeks was viewed as positive for acute crisis. We used two different prediction algorithms (Decision tree, Logistics regression) to predict whether a veteran would miss his or her discharge survey based on his/ her weekly participation and symptoms worse during this participation. Same procedure was followed using first five weeks data of participation and symptoms and first seven weeks data of participation and symptoms separately. To find the best approach for this prediction, we used cross-validation technique.

TABLE II. Comparison of Two different algorithms

	Cross- validation error		
Algorithms	***3 Weeks***	***5 Weeks***	***7 Weeks***
Decision Tree	29%	31%	22%
Logistic Regression	27%	17%	30%

The comparison table shows that a better prediction by decision tree method can be made using seven weeks participation data and symptoms information. A pruned decision tree based on first seven weeks information is given in Figure 1. This may actually help the mentor veterans to decide when to increase contact with their mentees in order to avert later crisis.

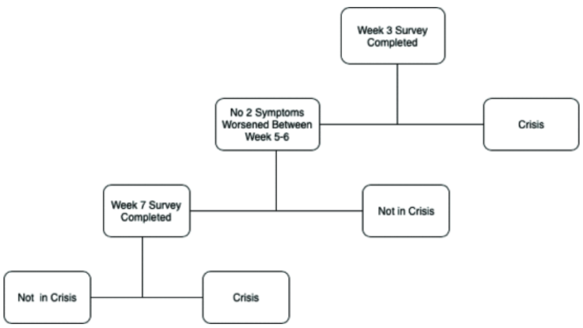

Fig1: Decision Tree for Clinical Decision Using Separate Seven Weeks Data

We estimated the accuracy, sensitivity and specificity of this decision tree in the confusion matrix in Table III. Among the 143 PTSD veterans, we had considered for this analysis, 114 of them had been correctly classified as “Crisis” and “Not in Crisis”. We had found that among the 97 veterans, it had classified as “Crisis”, 83 of them are really in long term crisis. On the other hand, we found that among 46 veterans which it had classified as “Not in Crisis” 31 of them are really “Not in Crisis”. The accuracy, sensitivity and specificity of the decision tree model are 79.7%, 85.4% and 67.4% respectively.

TABLE III. Confusion matrix

	Predicted Crisis Status			Total
		Crisis	Not in Crisis	
Actual Crisis Status	Crisis	83	15	98
	Not in Crisis	14	31	45
Total		97	46	143

According to this tree, if a veteran misses his/ her week 3 survey, he or she is going to miss the discharge survey. On the other hand, if he or she does not miss week 3 survey and 2 symptoms got worse between week 5 and week 6, then he or she would not miss discharge survey. However, if he or she does not miss week 3 survey, 2 symptoms do not get worse between week 5 and week 6 and they miss week 7 survey, then he or she may miss discharge survey. On the other hand, if the veteran does not miss week 7, they likely will not miss discharge survey. A different approach was also considered where we took total participation of veterans in the weeks and the total number of occurrences of 2 symptoms worse in consecutive two weeks as predictors. This means, in case of first three weeks for each PTSD veteran we considered how many weeks they had participated in the survey and how many times within these three weeks their 2 symptoms got worse between two consecutive weeks. Like before, we did this for first five weeks and first seven weeks separately. In Table IV, we made a comparison of predicting whether a veteran would miss discharge survey using these new features.

TABLE IV. Comparison of Two different algorithms

Algorithms	**Cross- validation error**		
	3 Weeks	***5 Weeks***	***7 Weeks***
Decision Tree	31%	31%	23%
Logistic Regression	17%	28%	16%

Table IV shows that a better prediction can be made by using logistic regression when we use first seven weeks data after their intake. However, for the convenience of our peer mentor veterans we would like to use the decision tree with first seven weeks data as it had the least cross-validation error among the decision trees, we had considered.

This decision tree suggests that if a veteran misses more than 5 weekly surveys within the first seven weeks of after his / her intake then he or she is likely to have a long-term crisis of missing the discharge survey. However, if he or she misses less than 5 weekly surveys and all the symptoms are not stable between all two consecutive weeks then he or she will not miss the discharge survey. However, if all the symptoms are stable but missed any weekly survey then he /she may miss the discharge survey. On the other hand, if he or she completed all the weekly survey then he or she may not miss the discharge survey.

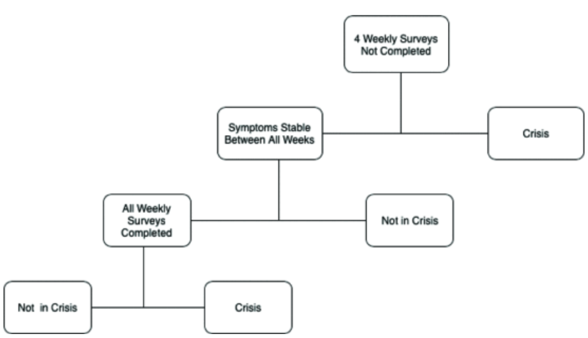

Fig2: Decision Tree for Clinical Decision Combined Seven Weeks Data

We estimated the accuracy, sensitivity and specificity for this decision tree using seven weeks data. We got the same results as before when we considered these seven weeks separately.

SECTION VI. Conclusions

In this paper, we proposed a way to predict long-term crisis among PTSD veterans using number of surveys misses and other events that we identified in the paper. This research emphasizes assisting peer mentors to take effective clinical decision. The main objective was to correctly identify whether a veteran will miss the discharge survey or not. For these reasons, two classification methods (Decision Tree and Logistic Regression) had been applied here. We believe that an easy way for peer-mentors to predict whether their fellow mentees are on long term crisis or not is to use a set of rules which incorporates the mentees' participation in the weekly survey and their conditions. We used decision tree approach for this purpose and hope that this would be a more effective way for our peer mentors to take clinical decision regarding their mentee veterans. However, the false negative rate can still be considered as little bit high. In future, we would like to come up with algorithms which can reduce this false negative rate. One other goal is to predict crisis as early as possible with significant accuracy. In the near future, we would like to consider whether we can use demographic characteristics of veterans to predict crisis at the intake, or to combine demographic data with weekly data to ensure that warning signs are identified as early as possible in the intervention. This approach supports attempts to advance understanding in precision behavioral health for US military veterans who are at high risk for mental health problems and difficulty with reintegration into civilian life.

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