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Recommended Citation

Hossain, Md Sazzad; Annapureddy, Priyanka; Ahamed, Sheikh Iqbal; Madiraju, Praveen; Flower, Mark; Rein, Lisa; Kissane, Thomas; Frydrychowicz, Wylie; Bansal, Naveen K.; Jain, Niharika; Hooyer, Katinka; and Franco, Zeno, "Implementing Algorithmic Crisis Alerts in mHealth Systems for Veterans with PTSD" (2020). *Computer Science Faculty Research and Publications*. 45.
https://epublications.marquette.edu/comp_fac/45

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Implementing Algorithmic Crisis Alerts in mHealth Systems for Veterans with PTSD

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ABSTRACT

This paper seeks to establish a machine learning driven method by which a military veteran with Post-Traumatic Stress Disorder (PTSD) is classified as being in a crisis situation or not, based upon a given set of criteria. Optimizing alerting decision rules is critical to ensure that veterans at highest risk for mental health crisis rapidly receive additional attention. Subject matter experts in our team (a psychologist, a medical anthropologist, and an expert veteran), defined acute crisis, early warning signs and long-term crisis from this dataset. First, we used a decision tree to find an early time point when the peer mentors (who are also veterans) need to observe the behavior of veterans to make a decision about conducting an intervention. Three different machine learning algorithms were used to predict long term crisis using acute crisis and early warning signs within the determined time point.

Keywords

Crisis, Machine Learning Algorithms, mHealth, PTSD.

INTRODUCTION

In this paper, it is demonstrated that by implementing different machine learning algorithms into a mobile-health app, alerts of PTSD-related crisis situations can be made with reasonable accuracy. An implementation of such technology is urgently needed, especially after the 9/11 terror attack, when many United States military service members have been deployed to war zones such as Afghanistan, Iraq and Syria. These service members have experienced different types of trauma events during their service which caused them to suffer severe mental health problems including PTSD. Military veterans suffering from PTSD have a higher chance of engaging in a variety of risky behavior such as alcohol abuse, impulsivity, and aggression (James *et al.*, 2014). Such behaviors may lead to violence, suicide and unintentional injury, causing harm to themselves and people around them. An estimate showed that a total of around 19.6 million veterans are currently living in the U.S. (Semaan *et al.*, 2016). Another study claimed that 19-42% of veterans returned from recent conflicts are suffering from different types of mental illness, among them 31% from Iraq and 11% from Afghanistan are diagnosed with PTSD (National Institute of Health, 2015).

Veterans, in general, suffer personal crisis more frequently than their non-veteran counterparts (Kang *et al.*, 2016; Novaco *et al.*, 2015). In one study, it has been found that about 22 veterans commit suicide every day (Semaan *et al.*, 2016). Another study found that over 60% of veterans suffering from PTSD had difficulties managing their expenses, 42% had difficulties obtaining medical assistance, and about 41% were struggling with alcohol and drug craving (Parker *et al.*, 2019).

In Milwaukee, Wisconsin, a veteran-led non-profit organization known as DryHootch (DH), established a community-based treatment system outside the traditional Veterans Affairs (VA) clinical environment (Rizia *et al.*, 2014). Initially, this peer mentor support program was purely face-to-face, and was later supplemented with online data capture. Subsequently, a mobile based application called Quick Reaction Force (QRF) was carefully designed for the program and continues to be used (Rizia *et al.*, 2015). Ecological Momentary Assessment (EMA) approaches were implemented into the QRF application to capture data from veterans via smartphone. The intervention occurred over a 12-week period during which the EMA approach captured repeated measures related to health, sleep quality, feelings, and engaging in risky behavior.

Based on the opinions of subject matter experts, early warning signs, acute crisis and long-term crisis were defined from this data with careful considering several aspects. The present research focuses on determining an optimal early time point at which peer mentor veterans should intervene so as to prevent a veteran dropping from the peer mentorship program.

Mobile Based Clinical Support

In order to encourage patients to maintain a healthy lifestyle, the health care providers need to maintain regular contact and provide consultation to their patients. In a number of settings, providing face to face consultation might be difficult. In such circumstances, mobile technologies can be used to obtain information about the patient's status and intervene remotely when required. A research study found that mobile based interventions via text messaging increased acceptance in areas like smoke cessation (Free *et al.*, 2013) and in improving medication adherence among teenagers with chronic health conditions (Badawy *et al.*, 2017); in another research, optimism had been expressed regarding ways in which data visualization can be used to improve mental health via mobile applications (Mohr *et al.*, 2013).

Mobile devices are also used to make clinical decisions. With the development of mobile devices, many important tasks of healthcare professionals have become easier, such as maintenance and access of health records, and better time management (Ventola, 2014). To diagnose, treatment and monitor diabetes mellitus a web and mobile clinical decision support tool was developed (Kart *et al.*, 2017). In one, study it has been claimed that the use of mobile based clinical support tool like PedsGuide had decreased the cognitive load in managing febrile infants (Richardson *et al.*, 2019).

Veteran Community Engagement

This work is part of larger project using a Community Based Participatory Research (CBPR) perspective and involves members of Dryhootch, faculty from the Milwaukee Veteran Affairs Medical Center and the Medical College of Wisconsin. The project had been working collaboratively with Dryhootch of America for several years to develop a mobile based app to support peer mentor veteran mental health intervention. The descriptions of this partnership, the Dryhootch Partnership for Veteran Health, its formation, and lessons learned are detailed elsewhere (Franco *et al.* 2016).

One focus of this program was to improve the outreach to younger veterans returning from Operation Enduring Freedom (Afghanistan) and Operation Iraqi Freedom (often referred to as "OEF/OIF veterans") using technology.

Typically, OEF/OIF veterans have different expectations from other US military service eras when interacting with various systems of care, often preferring technology-mediated contact (Franco *et al.*, 2018). The whole impetus for this project was to establish trust/mutual relationship between peer mentors and fellow mentees based on communication. One of the main objectives of building the QRF app was to facilitate more effective means of communication between peer mentors and veterans. Also, this app is designed to improve peer mentors' decision making regarding when to intervene (i.e. communicate) with veterans in response to early warning signs as visualized in the app.

In case of veterans with PTSD, the symptoms of crisis gradually increase if it is overlooked. This can potentially lead to engaging in harmful risky behaviors identified as crisis situations (e.g. suicide, alcohol abuse, fight in public places, etc.). Peer mentor veterans are trained to have conversations with their mentees at appropriate times, with the goal of significantly reducing the escalation of mentee symptoms. A secondary benefit of this communication is that peer mentor veterans can provide guidance to their mentees about when to contact a professional clinician (or help them with any other referrals) in order to get more appropriate care. Because of the nature of the illness, veterans with PTSD symptoms may not often be able to make proper decisions about themselves when it is really needed. The intent of the QRF app is to reduce the impact of PTSD significantly with time and cost efficiency, both at a personal and community-wide level. As part of this intervention, different machine learning algorithms were used to determine the earliest possible time point within which their behavior will reflect at the end.

There are three goals of this paper addressed: 1) Finding time point for early intervention using decision tree; 2) Predicting long term crisis using three different machine learning algorithms; and 3) Comparing the results from these algorithms. These goals were determined in order to improve the existing mobile based app to support peer mentors to make appropriate decision at appropriate time.

METHOD

In general, crises may be considered as events that lead to dangerous and unstable situations which may affect individuals, groups and even society. When we use the term "crisis", we mean some negative changes have occurred that require our immediate attention. Specifically, in psychology, Jacobson sees "crisis" as any stress that might have been caused due to some frightening experience or anxiety and builds his crisis theory as a framework based on which an intervention can be made. He goes on to state that a crisis occurs when psychological equilibrium is upset by life events. Thus, the goal of interventions is to create a new equilibrium which includes the most possible adaptive resolution (Jacobson, 1980).

Crisis theory is also commonly associated with reactions to natural disasters. Though a person's mental health crisis may differ in many ways on the surface, they share some common criterion such as 1) known or unknown pre-existing system vulnerabilities (Arnal, 2015); 2) early warning signs related to crisis which are difficult to define (Berariu *et al.*, 2015); 3) cascading effects as resources and options destroyed (Boettiger *et al.*, 2012); 4) a critical point beyond which control of situation decrease significantly (Camara *et al.*, 2013); 5) a well-defined crisis event requires significant external resources in order to recover or restore order (De Fina *et al.*, 2011).

Predicting such crisis events is a very challenging task as an inaccurate prediction may lead to serious consequences (Franco *et al.*, 2016). Within the research team, subject matter experts had defined the early warning signs, acute crisis and long-term crisis from our data driven perspective in the following ways:

Early Warning signs:

1. Any single weekly survey missed
2. Two symptoms indicated as worse in a single week

Acute Crisis:

1. Two consecutive weekly survey misses.
2. Any three weekly survey misses.
3. Three symptoms indicated as worse in a single week.
4. Two symptoms indicated as worse for two consecutive weeks.

Long Term Crisis:

1. 12-week Discharge PTSD score remain stable or worse.
2. Failure to complete 8 of 12 weekly surveys.
3. Missed discharge survey.

However, when attempting to predict the long-term crisis based on early warning signs and acute crisis using machine learning algorithms, it was found that the way it had been defined caused some of them to overlap with each other, thus creating intercorrelations. The underlying intercorrelation problem between some types of early warning signals and the crisis outcome is both a theoretical problem in terms of parsing the differences between two inter-related things with fundamentally similar qualities, and a statistical difficulty in trying to apply machine learning algorithms for prediction. For this reason, at least at this stage, it was decided to consider the early warning signs, acute crisis and long-term crisis that were not overlapping. In this research, the following criteria were used to define early warning sign, acute crisis and long-term crisis:

Early warning sign: Any one weekly survey missed.

Acute crisis: Any two symptoms getting worse in two consecutive weeks.

and **Long-term crisis:** Missing discharge survey.

PARTICIPANTS

305 US veterans had been enrolled in this community-based veteran peer mentorship program. The data for this analysis was collected both online using RedCap and through the QRF mobile app. The whole program was 12 weeks long consisting of three equidistant time points: baseline (beginning of the intervention), midpoint (at 6th-week) and discharge (at 12th-week). Several psychometric instruments like the Values in Action (VIA) scale, specific subscales of the Deployment Risk and Resilience Inventory (DRRI-2), Social Adjustment Scale (SAS), and the PTSD Checklist-5 (PCL-5) were collected at each timepoint.

For this paper, our focus was on PCL-5 score (a 20-item self-assessment tool) which contains components to measure four clusters of PTSD symptoms like intrusion, avoidance, negative emotions and arousal. PCL-5 score over 33 is considered as a provisional diagnosis for PTSD by the Veterans Affairs Healthcare System (VA). This study also consists of weekly EMA surveys in between these three time points where the veterans had been asked short questions regarding their health, sleep quality, stressful experience, whether engaged in risky behavior, and whether or not they were able to contact their mentor veterans. 143 veterans of the 305 veterans who participated were found to meet the cutoff score (PCL-5>33) of PTSD. Participant characteristics for the veteran sample with provisional prognosis of PTSD is provided here (Table 1). The group consists of 114 male veterans and 28 female veterans. Among these 143 veterans with probable PTSD, 34 were found to be enrolled into some school program. This veterans population consisted of service men and women from different branches of the military: Army, Navy, Marines, Air Force, Coast guard, National guard, and reserves. Based on the opinion of subject matter experts in our team, we considered army, marines, active as combat force and the remaining ones (Air Force, Navy, National guard and Coast guard) as less combat forward forces. According to this criterion 106 of these veterans fall into combat force and the remaining 37 veterans fall in non-combat force category. This population of veterans had different war experiences as they served in different eras, with the majority serving in the Iraq and Afghanistan war. However, a significant portion of these veterans declined to respond to the item about their war experience.

Table 1. Participant Characteristics

Characteristics	Count (%)
Gender	
Female	28 (19.6%)
Male	114 (79.7%)
Transgender/Missing/Unknown	1(0.7%)
School Enrollment	
Yes	34 (23.8%)
No	99 (69.2%)
Not Answered/Missing	10 (6.9%)
Military Branch	
Combat Force	106 (74.1%)
Non-Combat Force	37 (25.9%)
War Experience	
Post 9/11	48 (33.6%)
Vietnam	11 (7.7%)
Cold War	1 (0.7%)
Central America	3 (2.09%)
Gulf Era	12 (8.39%)
Not Answered/Missing	68 (47.6%)

Features: As predictors, consideration was made of the total number of weekly surveys missed within a fixed number of weeks (For early warning signs), as well as the number of times two symptoms labeled as worse for two consecutive weeks (For acute crisis). For example, for weekly participation:

Week1: Missing the first Week or not (0 or 1).

Week2: Number of weekly surveys missed within the first two weeks (0-2).

Week3: Number of weekly surveys missed within the first three weeks (0-3).

Similarly, *Week12*: Number of weekly surveys missed within the 12-week period (0-12).

On the other hand, for symptom change, we considered the following variables:

Symptom2: Any 2 symptoms got worse within the first 2 weeks or not (0 or 1).

Symptom3: Number of times any 2 symptoms got worse within the first 3 weeks (0-2).

Similarly, *Symptom12*: Number of times any 2 symptoms got worse within the 12-week period (0-11).

In this research, the outcome of interest is whether veteran will miss the discharge survey or not.

Machine Learning Algorithms for Predictions

To identify veterans who would be “in Crisis” and who would be “Not in Crisis”, three machine learning algorithms were considered: decision tree, logistic regression and naïve Bayes. A short description about how these algorithms work is provided here.

Decision Tree: This is a tree-like model to make decisions. The algorithm contains conditional statements to predict possible outcomes. This algorithm is applicable for both regression and classification problems. First, it divides the predictor space into several simple regions. It estimates the mean or mode of outcome of interest depending on whether it is quantitative or qualitative from training data at each region. This is used to predict a new observation. The whole process of dividing the predictors’ space can be summarized in a tree like structure which is why this method is known as decision tree (James *et al.*, 2013). It can be used to select variables. We had used decision tree to select the number of consecutive weeks within which we would observe the behavior of veterans to make appropriate classification. We used the information of selected number of weeks using decision tree.

Logistic Regression: A statistical model which uses probability to predict binary (0 or 1) outcome to make a simple yes or no classification. The binary outcomes are labeled as “0” or “1”. The probabilities of the outcomes are estimated by a function called logistic function. Logistic regression fits linear regression model of the log-odds on the predictors. For an observation, the log-odd is calculated from the regression line based on the values of independent variables and then using some algebraic manipulation, probability of belonging to label “1” is determined. For final classification a rule of thumb can be used as if the calculated probability is greater than or equal to 0.50 then the observation is labeled as “1”, otherwise it is labeled as “0” (James *et al.*, 2013).

Naïve Bayes: A probabilistic classifier which uses “Bayes Theorem” to make binary or multinomial classification especially when the independent variables are categorical. For classification of any observation, naïve bayes uses the conditional probability of predictors given the class and some prior knowledge of the probability of the class. It assigns the class final class for an observation which has the highest probability.

Algorithm Assessment Techniques

In order to decide which algorithm will make better prediction in identifying veterans with “in Crisis” or “Not in Crisis”, assessment tools were used including: 10- fold cross-validation, false positive rate, false negative rate and area under ROC curve.

Cross-validation: This is a recursive process to evaluate machine learning algorithms. Cross-validation process is mainly two types: *k*-fold cross-validation and leave-one-out cross-validation. The *k*-fold cross-validation divides the whole data into roughly equal size parts, *k*. The model or the algorithm which would be evaluated, is

fitted on $k-1$ parts and then it is evaluated on the k -th part. This process is repeated until all the observations are covered. At the end, mean number of errors is calculated. In case of leave-one-out, the same process is followed, with difference being that the model is evaluated on only one observation each time (James *et al.*, 2013).

False Positive Rate: This is the proportion of all negative observations that are classified as positive by the machine learning algorithms. In our case, it would mean that the proportion of number of veterans who are actually “Not in Crisis”, but the machine learning predicted them as “in Crisis”. In other words, we can say that this is a result from “false alarm”.

False Negative rate: This can be defined as the proportion of all positive observations that are classified as negative by the machine learning algorithms. In this case, it represents the proportion of number of veterans who are, in actuality, “in Crisis” but the machine learning predicted them as “Not in Crisis”.

Area Under ROC curve: In case of classification, Area Under ROC curve (AUC) is a measurement tool to evaluate the performance of algorithms. It tells how well the machine learning algorithm can distinguish between classes. It has values between 0 and 1 with higher values indicating that the algorithm is better in distinguishing classes.

RESULTS

RStudio (version 3.6.1) was used to run the analyses, setting the seed for programming to be 100. At first, the decision tree using all the predictors (weekly participation and symptom change) was used. The goal was to find the predictors which had more predictive capabilities than the others. The decision tree picked *Week3* as the top node of the tree (Figure 1). This means that the total number of surveys missed within the first three weeks had the highest predictive capabilities., This can be seen as an early time point within which it is necessary to observe the check-in behavior to determine whether a veteran would miss the discharge survey or not. In other words, the peer mentors need to carefully monitor the behavior of their mentee veterans within the first three weeks after they enter into the program in order to make appropriate decisions about intervention.

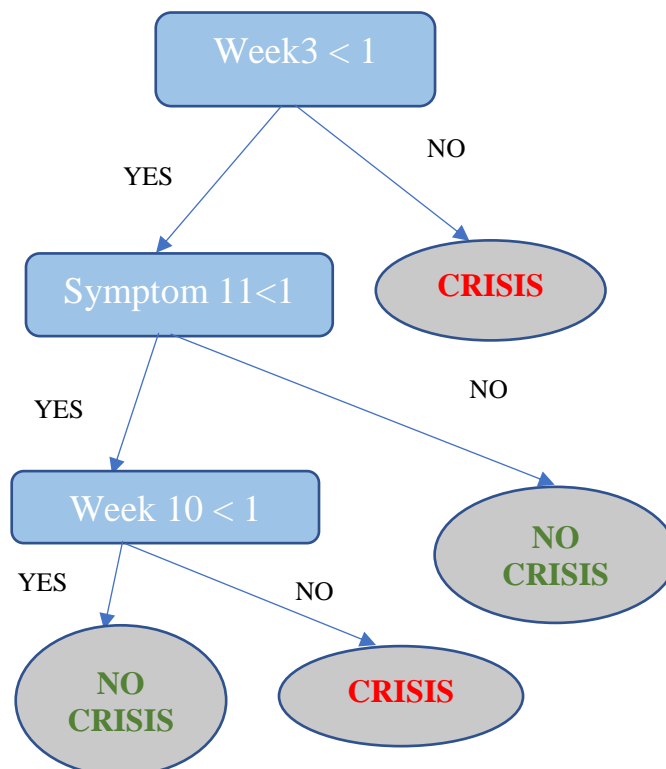


Figure 1. Prediction made by Decision Tree using Early Warning Signs (Missing Weekly Surveys) and Acute Crisis (2 symptoms worse for two consecutive weeks).

By pruning of the above decision tree (Figure 1), an illustration has been shown in Figure 2 about how this can be incorporated into the Quick-Reaction Force app which will aid the veteran mentors in making appropriate decisions about when to intervene. An empty hole represents a weekly survey missed and a dot represents that weekly survey is not missed. From the pruned decision tree, it was observed that if someone missed any of the weekly surveys within the first three weeks after the person enters the program there is a high chance that the person may drop from the discharge survey without giving any information (“in Crisis”). For the first veteran (JW) on the app (Left side of Figure 2), missed all the weekly survey within the first three weeks which creates an alert (!) notifying the peer mentor. The second veteran on the app (JM), missed the second weekly survey within the first three weeks which also creates an alert (!). However, the third veteran (RT), did not miss any weekly survey which indicates of potentially no threat (✓). Forth veteran (RL), missed two weekly survey (1st and 2nd) within the first three weeks which also created an alert (!) to the peer mentor.

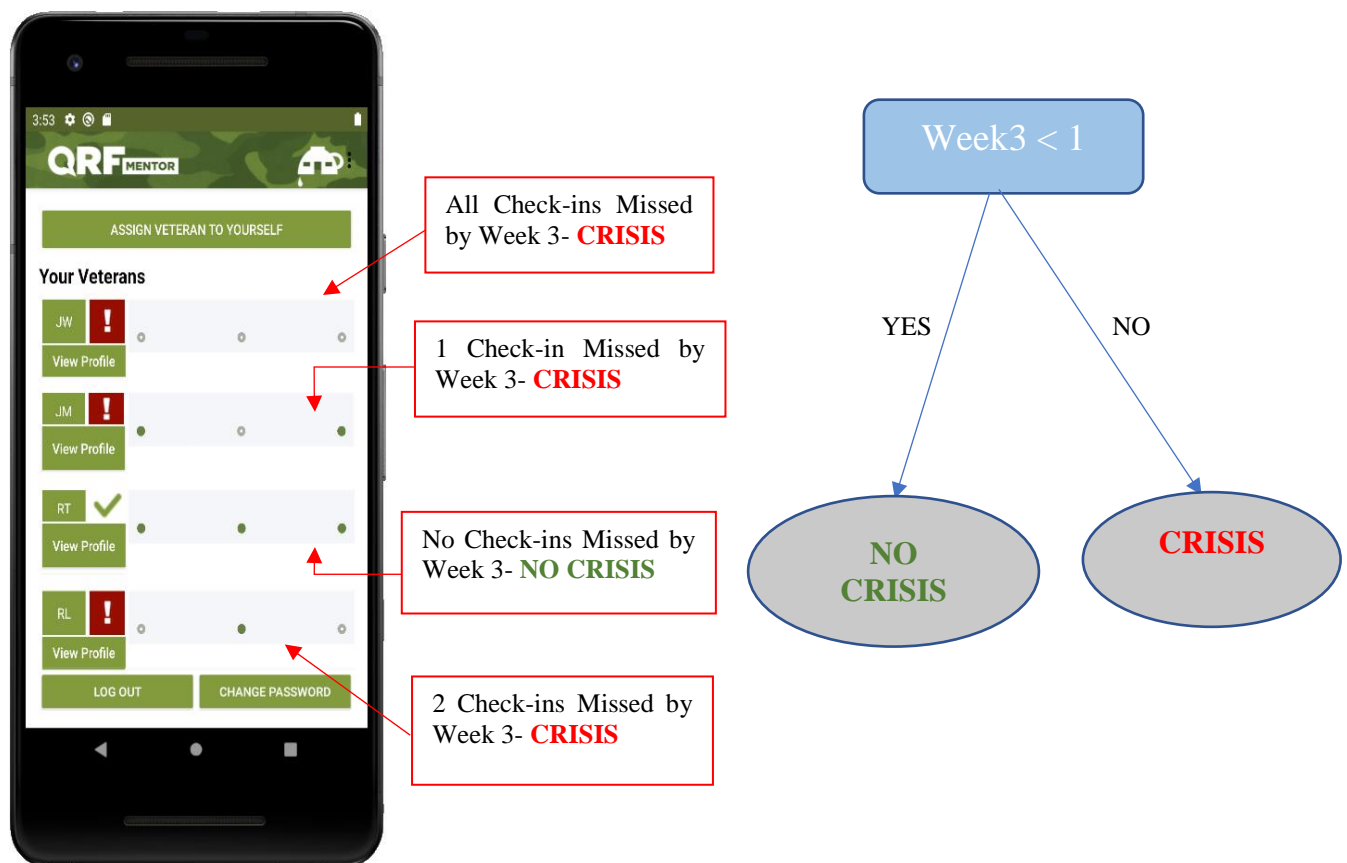


Figure 2. A Prototype of Quick-Reaction Force App Alerts (Left) and Decision Tree to select the time point (Right).

Next, an effort was made to determine what algorithm would perform better in predicting which veteran is going to miss the discharge survey. Two other algorithms were also considered (Logistic regression and naïve Bayes) for classification purpose besides decision tree.

In this case, each weekly survey participation (Early Warning Signs) were considered and each time 2 symptoms were indicated as getting worse for 2 consecutive weeks (Acute Crisis) as separate binary predictor. For example, in case of early warning signs, the binary predictors were considered as follows:

Miss1: Whether week one survey was missed or not.

Miss2: Whether week two survey was missed or not.

Miss3: Whether week three survey was missed or not.

Similarly, in case of acute crisis, the binary predictors were considered as follows:

Symptom_2: Whether two symptoms got worse between Week one and Week two.

Symptom_3: Whether two symptoms got worse between Week two and Week three.

Since the original decision tree had indicated that the first three weeks of check-in behavior reflects the behavior of the discharge survey, the binary predictors within the first three weeks were considered for later prediction. During the second time, when the decision tree was fitted using the data within the first three weeks, it is observed that more weight was put only on the week three participation.



Figure 3: Decision tree based on the data within the early time point.

This indicates that if a veteran misses the week three survey, he or she may potentially miss the discharge survey. From the analysis of the logistic regression on the same data, it is observed that besides week three participation, week one and two symptoms indicating stable or worse are significant.

Table 2. Logistic regression Analysis

	Coefficient	Std. error	Z-statistic	P-value
Intercept	0.0984	0.270	0.364	0.716
Miss1 [Yes]	-2.328	0.865	-2.691	0.007
Miss2 [Yes]	1.853	1.233	1.503	0.133
Miss3 [Yes]	-2.511	1.086	-2.314	0.021
Symptom2 [Worse]	-1.528	1.432	-1.067	0.286
Symptom3 [Worse]	2.412	1.196	2.017	0.044

In case of logistic regression, the following logistic function was used to estimate the probability of “Not in Crisis”:

$$P(Y = \text{Not in Crisis} | \text{Early Warning Signs, Acute Crisis}) = \frac{e^{0.098 - 2.328\text{Miss1} + 1.853\text{Miss2} - 2.522\text{Miss3} - 1.528\text{Symptom2} + 2.412\text{Symptom3}}}{1 + e^{0.098 - 2.328\text{Miss1} + 1.853\text{Miss2} - 2.522\text{Miss3} - 1.528\text{Symptom2} + 2.412\text{Symptom3}}}$$

A simple decision rule can be if the probability estimated from this logistic function is greater than 0.50, then that veteran can be classified as “Not in Crisis”.

From the naïve Bayes following confusion matrix was obtained. Among the 98 veterans who were actually in “Crisis” situation, 69 of those were correctly predicted as “Crisis” with a recall (69/98) rate of 70% and 37 veterans among 45 veterans who were “Not in Crisis” correctly predicted as “Not in Crisis” with a precision rate (37/45)

of 82%. The overall accuracy rate from naïve Bayes is 74.1%.

		Predicted Status		
		Crisis	Not in Crisis	Total
Actual Status	Crisis	69	29	98
	Not in Crisis	8	37	45
		77	66	143

Table 2 shows a comparison among these three algorithms (decision tree, logistic regression and naïve Bayes) using cross-validation error, false positive rate, false negative rate and area under ROC curve. These assessments were made on the same dataset as the algorithms were built on, meaning that that the training set and the testing set were the same.

Table 2. Algorithm Assessment

		Decision Tree	Logistic Regression	Naïve Bayes
Error Rate	Cross-Validation	29.4%	29.5%	29.4%
	False Positive	20%	20%	17.8%
	False Negative	28.6%	28.6%	38.8%
Accuracy Rate	AUC	75.7%	75.7%	71.7%

DISCUSSION

The cross-validation error rate from all three algorithms was close to 29.5% which means that in the long run if any of these algorithms are used for classifying 100 veterans, around 30 veterans would be misclassified. In Table 2, all three algorithms are giving better results than others in some cases. However, the differences are not significant. The false positive rate is around 20% which means that if we use these algorithms, 20 veterans among 100 veterans were falsely classified as “in crisis”. The false negative rate for decision tree and logistic regression was around 28.6%, but for naïve Bayes, it was 38.8%. False negative rate of 28.6% indicates that if we use decision tree or logistic regression, then about 29 veterans among 100 veterans who were predicted as “not in crisis” actually would be “in crisis”. For the clinicians in the team, this is an alarming rate as if a veteran in “Crisis” situation is missed to intervene properly, he or she might cause harm themselves and the people around them. Area under ROC curve (AUC) was also used as an effective tool to compare false positive rate and false negative rate of different methods. The AUC from these three algorithms was around 75% (or 0.75). It can be observed from Table 2 that there is no significant difference among these algorithms in terms of predictive performance.

CONCLUSION

In this research, an effort was made to identify veterans dropping from the program using early time point data by predicting which veteran will be "in Crisis" or "Not in Crisis". Decision tree, logistic regression and naïve Bayes algorithms were used to assess early time point data pre-determined by running a decision tree on the entire set of features. Different types of model assessment techniques including cross validation, false positive rate, false negative rate, and area under ROC curve to were used to determine which model was most effective. However, the experts on our team felt that the assessments did not reveal any of these three algorithms to out-perform the others in term of predictive power. In the future, crisis will be defined based on the lived experiences of Veterans who have experienced mental health crisis. This will be accomplished through focus group interviewing methods

and analysis will emphasize identifying a more personalized alert system using machine learning algorithms. Based on the analysis of this data, a mobile app will be developed to trigger tailored and more accurate alerts for peer mentors. It will notify a mentor when a mentee under their observation might be in risk for crisis. This system might be useful in other areas such as preventing risky behavior linked to substance abuse, domestic violence, and dementia, in both developing and less-developed countries.

ACKNOWLEDGMENTS

We would like to thank DryHootch of America for help and cooperation. This project was supported by the National Center for Advancing Translational Sciences, National Institutes of Health, Award Number UL1TR001436. Also, the project was partially funded by the Research and Education Program Fund and the Healthier Wisconsin Partnership Program, components of the Advancing a Healthier Wisconsin endowment at the Medical College of Wisconsin.

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