Applying Machine Learning to Linked Administrative and Clinical Data to Enhance the Detection of Homelessness among Vulnerable Veterans

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U.S. military veterans who were discharged from service for misconduct are at high risk for homelessness. Stratifying homelessness risk based on both military service factors and clinical characteristics could facilitate targeted provision of preventive services to those at critical risk. Using administrative data from the Department of Defense and Veterans Health Administration for 25,821 misconduct-discharged Veterans, we developed a dataset that included demographic and clinical characteristics corresponding to 12-months, 3-months, and 1-month preceding the first documentation of homelessness (or a matched index encounter for those without homelessness). Clinical time-trend features were extracted and included as additional model inputs. We developed several random forest models to classify homelessness risk. Models based on 1- and 3-months of data performed roughly as well as those based on 12-months of data. In best-performing models, 70% of those identified as at high-risk became homeless; 30% identified as at moderate risk became homeless (AUC=0.80; recall=0.64, specificity=0.82). Findings suggest the viability of risk stratification for targeting resources.

Introduction

For many U.S. military Veterans, the transition to civilian life following discharge from service can bring significant challenges, including physical and mental health symptoms, and problems functioning at home, school, or work[1]. These challenges are often related to the unique occupational context of military service[2]. Thus, information regarding military service experiences and exposures is important for improving our ability to understand and anticipate post-discharge service needs. However, military service records and post-discharge records are largely maintained by separate entities (the Department of Defense and Veterans Health Administration), and are challenging to obtain and link for research purposes. One occupational factor that is strongly tied to difficulties during the transition period is having been discharged from military service for reasons related to misconduct. Veterans with misconduct-related discharges are at high risk for mental health and substance use disorders[3,4], and have 4-6 times higher risk for homelessness[5].

Primary prevention is an essential element of eliminating homelessness. A central challenge of prevention is effectively identifying those who will experience homelessness in the absence of intervention[6], as this is necessary for the targeted provision of limited resources to those at critical risk. Although misconduct-discharged Veterans are heavily overrepresented among the homeless, homelessness is still a relatively uncommon event. Further, homelessness is often episodic, and risks fluctuate over time[7]. Thus, even among this high-risk group, the proportion of individuals at critical risk at any given point is likely low. For these reasons, surveillance strategies that take time-varying circumstances into consideration are needed to refine risk stratification estimates.

Previous research has demonstrated the utility of administrative clinical data in the prediction of several adverse outcomes, including suicide[8,9], drug overdose[10], unintentional injury[11], and homelessness[12]. Recorded in the electronic medical records of those seeking care at Veterans Health Administration (VHA) are a wide range of indicators with strong potential for discriminating risk for homelessness, including clinical diagnoses and health service utilization characteristics. The use of this rich clinical information in predictive modeling in conjunction with linked data from the Department of Defense represents a potential opportunity to improve the provision of timely and appropriate intervention to those who are at imminent risk for homelessness. Therefore, the purpose of this study was to use data from VHA and the Department of Defense to develop models to predict homelessness among veterans who were discharged from service due to misconduct.

Methods

Study Population

The database was created by merging national clinical data from VHA and the Department of Defense. VHA is the largest integrated health care system in the United States, providing care to over 9 million Veterans at 1,243 health care facilities nationwide[13]. Data from the Department of Defense was sourced from the Defense Manpower Data Center-maintained OEF/OIF Roster File. The Roster File includes demographic and military service information for Veterans who deployed to post-9/11 conflicts in Iraq and Afghanistan and separated from service through fiscal year (FY) 2012. Records from the Roster File were linked to VHA clinical data using scrambled social security identifiers, yielding a nearly perfect match.

The final analytic dataset included records for 25,510 VHA-enrolled veterans with a misconduct discharge who deployed to post-9/11 conflicts in Iraq and Afghanistan, separated from service through fiscal year (FY) 2012, and had at least one post-discharge VHA encounter. Demographic and military service data were extracted from an official Department of Defense roster file and included the following variables: age, sex (male, female), race (White, Black, Hispanic, other/unknown), education (no high school diploma/ diploma equivalency only, high school diploma, any college), marital status (never married, married, divorced/other), branch of service (Army, Navy/Coast Guard, Marines, Air Force), rank (enlisted, officer/warrant), exposure to combat (yes/no) and type of discharge (see section misconduct subtype below). Clinical service usage data through 2015 were extracted from the VHA Corporate Data Warehouse (CDW) using the VA's secure Informatics and Computing Infrastructure research workspace (VINCI)[14], and included frequencies for clinical diagnoses and outpatient and inpatient encounter records. Additional administrative military service variables including exposure to combat, military sexual trauma status, and service-connected disabilities were extracted from the Patient 2.0 Domain of the CDW.

Study Variables

Veteran Homelessness. Veterans were identified as having administrative evidence of post-deployment homelessness if they received an International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) code of V60.0 (indicating "lack of housing") as either their primary or other code during a VA visit, or a non-ICD VA clinic or specialty code related to the receipt of homeless services.[15]

Health Status. Clinical diagnoses were retrieved from VHA administrative data using primary ICD-9-CM codes recorded in outpatient and inpatient encounters. Classifications from the enhanced Elixhauser comorbidity index,[16] a widely used method for categorizing comorbidities, were used to create a set of 31 medical and mental health diagnostic indicators. In order to provide the algorithm with the maximum amount of information possible, Elixhauser variables were represented as the counts of diagnoses by category, rather than using typical binary coding of these variables. In addition to Elixhauser variables, diagnostic count indicators were created for ICD-9 codes of V62.5 (Legal Circumstances), and 309.81 (PTSD).

Healthcare Utilization. Utilization frequencies were for computed for both inpatient and outpatient care. Inpatient care was further stratified into the following categories based on treatment specialty codes: psychiatric, substance use, and medical. Outpatient care was further stratified into the following categories based on VHA clinic stop code classifications: mental health, substance use, primary care, emergency department/urgent care, social work, medical specialty, diagnostic, homeless services, polytrauma, veterans justice outreach, and other outpatient.

Military Sexual Trauma. As part of routine clinical care, all veterans are screened for military sexual trauma (MST). The screen consists of the following two items: "While you were in the military…a) Did you receive uninvited and unwanted sexual attention, such as touching, cornering, pressure for sexual favors, or verbal remarks? b) Did someone ever use force or threat of force to have sexual contact with you against your will?" Veterans may respond "yes," "no," or "decline" to either item. The screen is considered positive if a veteran responds in the affirmative to either item. Veterans who had no valid screen on file were retained in the sample, and assigned a value of "unknown" for this variable.

Service-Connected Disability. Records of disabling conditions that occurred as a result of military service were extracted from VHA clinical data. Service-connected disabilities are not directly entered as diagnosis codes, but a crosswalk file that links disability types to related ICD-9 and ICD-10 diagnoses is provided in the administrative database. Using these related diagnoses, service-connected disabilities were classified according to the Elixhauser

Comorbidity Index[16] into 31 categories of chronic health conditions based on ICD diagnosis codes found in administrative data. Notably, Elixhauser category "depression" contains the ICD code for post-traumatic stress disorder (PTSD). Due to the complex nature of the computation of service-connected disability percentages for individual disabilities, these variables were coded as binary, and were set to "0" until the time of their documentation, and "1" thereafter. In addition, a variable for total level of service-connected disability was extracted using the level recorded at the time of each clinical encounter. Values for total service-connected disability in the administrative database were coded into 3 categories consistent with previous literature,[17] including not service-connected, 1-49% service-connected, and 50-100% service-connected.

Misconduct Subtype. In order to examine potential differences between types of misconduct in the prediction of adverse outcomes among misconduct-discharged veterans, a variable for misconduct subtype was created using the following classifications of interservice separation codes recorded in the Roster File, including: drugs/alcohol, commission of a serious offense, discreditable incidents - civilian or military, alcoholism, discharge in lieu of court-martial, pattern of minor disciplinary infractions, and other.

Data Manipulation and Case Matching

A modified case-control design was used to create the analytic dataset. Veterans with any evidence homelessness during administrative follow-up were considered cases, while those with no evidence of homelessness were considered controls. The index date for cases was defined as the date of the encounter in which homelessness was first recorded. For controls, index dates were determined by selecting encounters that were matched to cases on the age of the clinical relationship (i.e., the time from the first VHA encounter to the index date). Then, retrospective follow-up data was extracted for the one year preceding the index date for both cases and controls.

Clinical variables (i.e., health status and healthcare utilization variables) from the one year of retrospective clinical follow-up were aggregated into sequential 30-day intervals in order to capture potential changes in clinical activity over the course of follow-up. Resulting variables reflected the sum of diagnoses and encounters for each 30-day interval. While standard machine-learning methods are not equipped to explicitly account for time-trends in longitudinal data, pre-processing of data was conducted to extract time-trend features from the data to be used as additional inputs to the model. Time-trend features were extracted using a variety of techniques, including regression, wavelet transform, and computation of simple mean differences.

The random forest machine learning technique was used to develop algorithms to classify homelessness as a function of demographic, military service, health status, and healthcare utilization characteristics. Random forest is an ensemble method in which many decision trees are grown from bootstrapped samples of the training data. At each node of a given decision tree, a random subset of predictor variables is selected, and the node is split based on the variable/split-point combination that results in the greatest gain in purity of the resulting nodes. This process is recursively repeated until the minimum node size is reached. When used for classification, a class vote is obtained from each tree for observations that were not used in the construction of that tree, and resulting prediction is based on the majority vote across the ensemble. This "out-of-bag" estimation is unbiased and prevents overfitting. Thus, a random forest can be fit in one sequence, and additional cross-validation or hold-out datasets are not required[18,19]. Random forest is well equipped to handle high dimensional data, correlated predictors, nonlinear effects, and complex interactions. In addition, it requires minimal tuning relative to alternative similarly performing algorithms, making it more easily adaptable to live data.

In order to address computational considerations pertinent to any future scaling-up of predictive algorithms, the tradeoff between accuracy and parsimony was evaluated by developing a range of models that varied in the number of included variables as well as the range of follow-up for which variables were included. Variable importance indices based on the Gini impurity index[18] were computed and used to identify well-performing variable subsets. Models were optimized through cross-validated comparisons of ensemble sizes, and number of variables tested at each split. Due to the imbalanced nature of the outcome variable, model-predicted probabilities were evaluated at various thresholds for prediction of the positive class, and final algorithms were selected based the Kappa statistic, AUC value, and recall.

For each outcome, final models based on 4 different variable sets were selected for comparison. These variable sets included the following: (1) **12-month: all variables**, including static demographic and military service

characteristics, clinical variables in 30-day intervals for all 12 months of follow-up, aggregated clinical variables, and trend indicators representing the difference between the first 9 months and the final 3 months of follow-up on the average rate of recorded encounters and diagnoses; (2) **12-month: aggregation and trends**, including static demographic and military service characteristics, clinical variables in 30-day intervals for the final 3 months of follow-up only, aggregated clinical variables, and trend indicators as described in 1; (3) **3-month: all variables,** including static demographic and military service characteristics and clinical variables in 30-day intervals for the final 3 months of follow-up; and (4) **1-month: all variables**, including static demographic and military service characteristics and clinical variables for the final 30-day interval of follow-up. Using model-predicted probabilities, all observations were assigned to a risk group. Individuals whose predicted probability for homelessness was less than .20 were classified as low-risk, those whose predicted probability was between .20 and .50 were classified as moderate-risk, and those whose predicted probability was greater than .50 were classified as high risk. Predicted risk class membership was then tabulated against actual evidence of homelessness. Finally, in order to compare the performance of these models to more parsimonious models, each model was recomputed using only its 20 most important variables as determined by the Gini impurity index.

Results

The sample was 92.2% male, with an average age of 26.9 years at the time of first VHA encounter; 58.0% were White, 25.4% were Black, 10.4% were Hispanic, and 6.1% were of other or unknown race/ethnicity. Approximately 72% had a high school education only, and 30.4% were married. Over 97% were of enlisted rank. Army was the most common branch of service, followed by Navy, Air Force, and Marines (62.0%, 19.0%, 10.2%, and 8.8%, respectively).

Table 1 includes homelessness classification model performance metrics for the 4 selected variable subsets. Model performance was similar across all subsets, with area under the receiver operating characteristic curve (AUC) values ranging from .792 to .802, and Kappa statistics ranging from .401 to .438. At the default positive class prediction threshold of .5, recall ranged from .410 to .434. With a lower threshold of .35, the range of recall improved considerably to a range of .611 to .637, and generally corresponded to increases to the Kappa. AUC values for simplified models that were re-estimated based on the 20 most important variables from the given variable subset as determined by the Gini impurity index. AUC values for these simplified models were attenuated, but still all exceeded .750. Figures 1 and 2 illustrate the comparison between predicted risk group and actual housing status based on the 3-month model.

Table 1. Random forest models classifying homelessness among misconduct-discharged veterans: performance across various sets of input variables and thresholds for positive class prediction

Threshold	Accuracy	Recall	Specificity	Precision	NPV	Kappa	AUC
12-months of clinical follow up: all variables (number of input variables= 319)							
Threshold = .50	.796	.410	.938	.708	.812	.401	
Threshold = .40	.788	.542	.877	.619	.839	.436	.798
Threshold = .35	.773	.611	.833	.574	.853	.435	
				*.763			
12-months of clinical follow up: aggregation and trends (number of input variables = 100)							
Threshold = .50	.796	.433	.929	.692	.816	.401	
Threshold = .40	.783	.565	.864	.605	.843	.438	.802
Threshold = .35	.769	.637	.818	.563	.859	.437	
				*.760			
3-months of clinical follow up: all variables (number of input variables = 81)							
Threshold = .50	.796	.426	.932	.698	.815	.408	
Threshold = .40	.784	.556	.867	.609	.842	.437	.798
Threshold = .35	.769	.622	.834	.565	.855	.432	
				*.772			
1-months of clinical follow up: all variables (number of input variables = 43)							
Threshold = .50	.794	.434	.927	.687	.816	.409	
Threshold = .40	.781	.563	.862	.601	.843	.434	.792

Threshold = .35	.764	.621	.816	.555	.854	.422
					*.776	

Notes: Accuracy = Percent correctly classified; Precision = Positive predictive value; Recall = Sensitivity; Specificity = True negative rate; NPV = Negative predictive value; AUC = Area under the receiver operating characteristic curve. Threshold values represent the model-predicted probability at which cases were classified as homeless. *Denotes the AUC value for a classifier based on the 20 most important variables from the given variable subset.

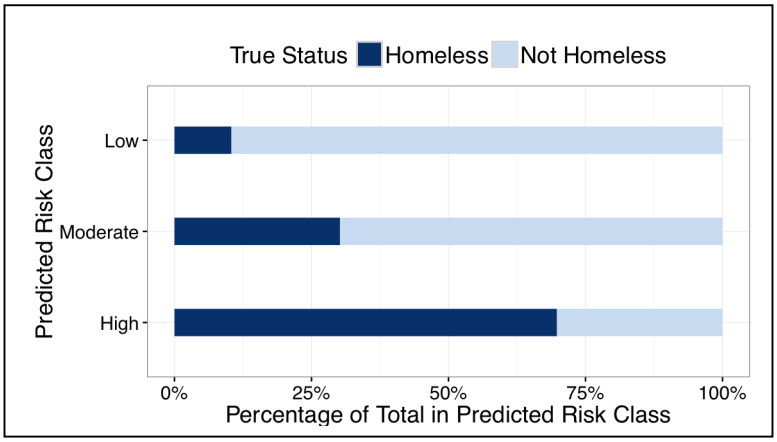

Figure 1. Predicted risk class vs. actual homelessness evidence

Despite the wide range of input variables included in each model, there was considerable consistency among the four models in terms of the variables determined to be important to the classification. In all four models, age at first VHA encounter, follow-up strata, age at first deployment, misconduct subtype, alcohol-related diagnoses, social work encounters, mental health encounters, depression diagnoses, and race/ethnicity were determined to be of high importance. In several cases, when variables that were not supplied to shorter-term models were identified as important in the longer-term models, theoretically similar indicators were identified as important in the shorter-term models. For example, in both 12-month models, aggregated representations of primary care encounters were identified as important, whereas in the 3- and 1-month models that did not include aggregated indicators, primary care encounters in the final month of follow-up were selected as important. Relative to controls, cases had higher rates of utilization and clinical diagnoses, and trend indicators suggested that utilization and diagnoses among cases increased more over the course of follow-up. While the majority of variables identified as important significantly differed between cases and controls in bivariate comparisons, a few did not, including follow-up strata, age at first deployment, marital status, and percent service connected.

In models based on original variable sets, 10-11% of those who were predicted to be at low risk were found to be homeless (N = 1,204 to 1,358), 29-31% of those who were predicted to be at moderate risk were found to be homeless (N = 2,528 to 2,690), and 69-71% of those who were predicted to be at high risk were found to be homeless (N = 2,924 to 2,977). In simplified models based on the 20 most important variables in each variable set, classification performance was again only slightly attenuated.

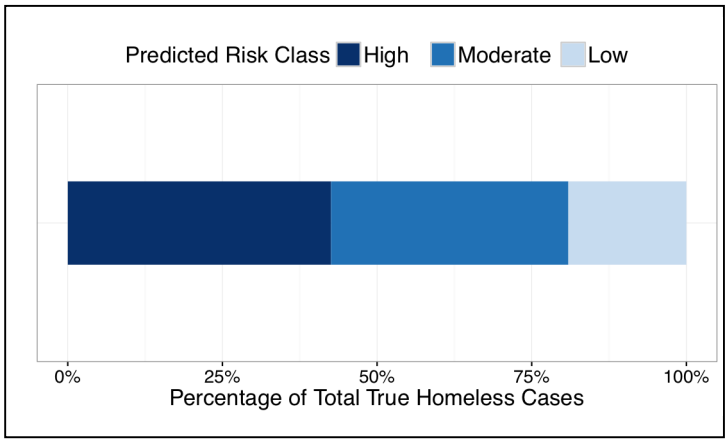

Figure 2. Risk class assignments among cases with evidence of

Discussion

Results from this study demonstrate that when data from VHA and the Department of Defense are combined, risk for homelessness among this vulnerable veteran population can be stratified via machine learning techniques using a limited number of indicators and relatively short period of administrative follow-up. Such a system offers practical utility in outreach and clinical care. Notably, engagement in specialty services, especially social work and mental health/substance use services, was a marker for imminent homelessness. Usage of these services and receipt of related diagnoses may reflect the deterioration of mental health or life circumstances that often precipitates adverse

social events like homelessness. These results indicate that many VHA-enrolled veterans who are at imminent risk for homelessness are actively engaged in care. Thus, there may be opportunities to integrate enhanced screening, referral services, or additional supports into the services that are already being used by at-risk veterans.

Machine learning models provided stable predictions that made use of high dimensional data and detected higher-order interactions. This is illustrated by the variables identified as important in the machine learning models. For example, although cases and controls were matched on follow-up stratum and there were no statistical differences between groups on this variable, follow-up stratum was consistently identified as a high-importance variable. By using this variable at multiple decision points in a given tree, the algorithm was effectively able to condition the effect of time-varying clinical variables on follow-up time, resulting in more sensitive indicators.

Comparisons across different machine learning models yielded several practical insights. First was the relative unimportance of pre-processing data for these classification tasks. While models that included aggregated variables or representation of time trends often identified these indicators as important, in their absence, very similar information was able to be extracted from the raw variables. It was also revealed that for homelessness, predictions based on 3 months or even 1 month of follow-up data are roughly as accurate as predictions based on 12 months of follow-up data. Next, simplified models that were based on the 20 most important variables for each subset, while inferior, still provided useful stratification information. Finally, little tuning of the models was required. While classifications improved with a larger number of trees, adjustments to the number of variables tried at each split did not strongly affect predictions. These are all attractive features, as they allow for simple retraining of the models, should additional indicators become available or of interest.

Predictive models suggest potential for flagging a large number of high-risk veterans. Based on the performance of the model that uses 3 months of data, among the 6,871 veterans who became homeless, 2,924 (44.6%) were predicted to be at high risk, 2,636 (38.4%) were predicted to be at moderate risk, and 1,311 (19.1%) were predicted to be at low risk. Thus, based on this model, over 80% of those who went on to become homeless were predicted to be at other than low risk. In practice, these risk tiers are flexible. For example, it may be sensible to include all veterans who were identified as moderate- or high-risk in the target group for a relatively simple to deploy and low-cost intervention. While a larger target group will necessarily result in a higher number of false positives, this may be acceptable for a low cost/low barrier intervention. Conversely, a more resource intensive intervention may be targeted to only those identified as high-risk.

Limitations

This study has several limitations. Results are based on veterans who are seeking treatment at VHA facilities, and not all veterans choose to use VHA services. During the period of follow-up for the present study, 63-65% of VHA-enrolled veterans used services each year.[20] Certain characteristics common misconduct-discharged veterans are associated with a lower likelihood of dual and non-VHA service use (lower levels of income and education)[21,22] suggesting that these veterans may be even more likely to be represented in our sample. Nonetheless, it is unclear how these results might relate to misconduct-discharged veterans who do not use VHA care. Even among veterans who had at least one VHA encounter and were thus represented in our sample, some are not regular users. These veterans likely make up many of those who were classified as low-risk, but went on to experience an adverse outcome. This highlights a persistent challenge VHA faces in delivering prevention efforts to veterans who are vulnerable, but not regular users.

It is also not possible to draw direct causal inferences from these models. The documentation of events in the medical record does not necessarily correspond to the true chronicity of exposures, the manifestation of symptoms, and outcomes. Further, administrative data fails to capture many important variables that fall outside of the general medical context. Due to the case control design used in this study, the ratio of cases to controls is higher in the analytic data than in live data. As a result, machine learning training set performance metrics are specific to this sample. In future applications of these techniques to live data, tuning may be required to optimize model performance for differently balanced classes.

Policy and Clinical Practice Implications

The integration of algorithmic analytic approaches into the clinical workflow is an example of a learning health care

system, an approach that has been comprehensively described by the Institute of Medicine,[23] and is advocated by AHRQ and Veterans Affairs leadership.[24,25] Even in the context of excellent patient-centered care, providers are unable to take in the vast amounts of information available regarding every veteran's demographic and military service background and clinical history, and subsequently accurately assess their needs across a range of health and social domains. In this way, risk stratification tools that provide up-to-date predictions can support providers in providing timely and appropriate clinical care and referrals.

This approach facilitates a shift from intervention toward prevention, which is very applicable to addressing homelessness. For example, a veteran may experience health or legal problems, leading them to fall behind on their rent. Based on that veteran's profile and clinical history, an alert can be generated in the electronic health record at the point of care, informing the front-line provider that the veteran may be at-risk for homelessness. The provider can then engage the veteran in conversation, assessing needs and discussing resources that may address those needs, and resolve the current instability. In the absence this brief intervention, the veteran may not be made aware of needed services, and their financial and health status may continue to deteriorate, ultimately resulting in eviction. Exacerbation of symptoms and unemployment may follow, and the situation likely becomes much more difficult and costly to resolve. Importantly, targeted service provision through risk stratification would not place limitations on service usage based on results; rather, it would help to improve access among those who are in need of services but may not necessarily be identified as such in the absence of these tools. In addition, risk stratification approaches may be useful at the policy-making level for service planning prevision, as predictions can aid in the targeted allocation of resources to regions and facilities where high service needs are anticipated.

Future Directions

Future research focusing on the implementation of risk management tools is also needed, including assessing provider and patient perspectives on adaptation of such a system, piloting and evaluating the algorithm performance on live data, and determining computational and systems requirements for broad adaptation. Ultimately, in a fully developed system, variations in treatment could be recorded and further analyzed to inform and improve care, leading to a continuous feedback cycle that encourages constant quality improvement.

Conclusion

Administrative data from VHA and Department of Defense contain many indicators that effectively predict risk for homelessness among veterans who were discharged from service for misconduct. The presence of recent specialty clinical service usage was particularly useful for estimating risk, suggesting that there may be opportunities to integrate relevant preventive services into the care that high-risk veterans are already receiving. We also found that risk for homelessness could be stratified using a limited number of indicators and relatively short period of administrative follow-up. These findings suggest the viability of risk stratification techniques for preventing homelessness among this vulnerable veteran population.

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