A CASE FOR DEVELOPING DOMAIN-SPECIFIC VOCABULARIES FOR EXTRACTING SUICIDE FACTORS FROM HEALTHCARE NOTES

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ABSTRACT

The onset and persistence of life events (LE) such as housing instability, job instability, and reduced social connection have been shown to increase risk of suicide. Predictive models for suicide risk have low sensitivity to many of these factors due to under-reporting in structured electronic health records (EHR) data. In this study, we show how natural language processing (NLP) can help identify LE in clinical notes at higher rates than reported medical codes. We compare domain-specific lexicons formulated from Unified Medical Language System (UMLS) selection, content analysis by subject matter experts (SME) and the Gravity Project, to data-driven expansion through contextual word embedding using Word2Vec. Our analysis covers EHR from the Veterans Affairs (VA) Corporate Data Warehouse (CDW) and measures the prevalence of LE across time for patients with known underlying cause of death in the National Death Index (NDI). We found that NLP methods had higher sensitivity of detecting LE relative to structured EHR (S-EHR) variables. We observed that, on average, suicide cases had higher rates of LE over time when compared to patients who died of non-suicide related causes with no previous history of diagnosed mental illness. When used to discriminate these outcomes, the inclusion of NLP derived variables increased the concentration of LE along the top 0.1%, 0.5% and 1% of predicted risk. LE were less informative when discriminating suicide death from non-suicide related death for patients with diagnosed mental illness.

Keywords: Natural Language Processing; Machine Learning; Electronic Health Records; Social Determinants of Health; Suicide Prevention; Predictive Modeling

1 Introduction

The rate of death by suicide among U.S. Veterans has risen by 35.9% since 2001 and is now nearly twice as high as the rate among non-Veteran U.S. adults (Department of Veterans Affairs, 2021). To address this crisis, the Veterans Health Administration (VHA) has been providing screenings and outreach programs to help identify and intervene with Veterans in need (Warren and Smithkors, 2020). It is leveraging its comprehensive electronic health records (EHR) database, which provides a unified nationwide ontology that integrates data across VHA institutions. Adoption of EHR has contributed to a substantial increase of structured information regarding demographics, medications, and billing codes, as well as unstructured clinical notes. Taking advantage of the large data, VHA has developed a model to predict Veterans' suicide risk, called REACH VET (RV) (McCarthy et al., 2015). Using only structured EHR (S-EHR) data to estimate patients suicide risk, RV's inferences inform healthcare providers about which patients are at the highest risk of dying by suicide and whether immediate outreach or increased preventative outpatient services is appropriate.

A substantial challenge in evaluating the performance of suicide risk models is the high imbalance between cases and controls. Typical measures for classification and information retrieval, like area under the ROC curve (AUC) and F1-score, provide suboptimal interpretations of model performance. Instead, McCarthy et al. (2015) measure the concentration of suicides across various percentiles of predicted risk, where the top 0.1% and 5.0% of predictions are considered to be at imminent risk and at-risk for suicide respectively. They found that RV's patient risk concentrations follow the rate of suicide in the patient cohort, providing a strong foundation towards risk prediction using EHR.

Life events (LE) like housing and job instability are among the top predictors of death by suicide and suicide attempts (Paykel, 1975; Gundlapalli et al., 2013b, 2019; Franklin et al., 2017). Paykel (1975) found that suicide attempters reported 4 times as many LE as individuals from the general population and 1.5 times as many as depressed patients prior to depressive onset. Franklin et al. (2017) identified LE as the 5th strongest longitudinal predictors of death by suicide from hundreds of variables considered in their meta-analysis of the past 50 years. Unfortunately, RV has low sensitivity to capture these LE due to the under-reporting in S-EHR data. Thus, extraction of LE has the potential to increase the identification of Veterans at risk for suicide.

To address this issue, Gundlapalli et al. (2013a, 2013b, 2019) developed natural language processing (NLP) methods to extract LE such as homelessness, marital troubles and military sexual trauma (MST). Brandt et al. (2021) used NLP to identify access to firearms from clinical notes. However, the methods used in all cases focused on either a subset of the VHA facilities or notes and did not address the big data challenges of utilizing NLP. Notably, Bejan et al. (2018) developed a large-scale method to extract homelessness and adverse childhood experiences from 100 million notes from a de-identified database.

1.1 Objective of the Present Research

The objective was to apply NLP to extract LE indicators from clinical notes in the VHA EHR to improve the identification of acute risk factors for suicide. We hypothesize that because a single LE can exacerbate ongoing mental health conditions, integrating these acute factors with well-known predisposing factors will improve the suicide risk models. To test this hypothesis, we focused on 9 LE that were identified by our VHA operational partners as variables that would

benefit from improved detection using NLP. They include housing instability, job instability, justice (troubles with the law), social connections (isolation and partner relationships), detoxification, MST, access to lethal means, and food insecurity. Two NLP methods for extracting LE indicators from the clinical notes were explored in this analysis: 1) a knowledge-based approach using a set of terms augmented from the Unified Medical Language System (UMLS) and 2) a data-driven approach using contextual word embedding for adding statistically similar terms. The prevalence of these events in the clinical notes was compared against signals extracted from S-EHR equivalents. These NLP-extracted LE indicators were then integrated with variables used in RV (McCarthy et al., 2015). This work is important because a) it demonstrates that large-scale NLP can be used to extract LE from VHA data, b) it integrates these factors with suicide risk models, and c) it potentially improves targeting patients who have experienced LE for outreach by clinicians.

2 Methods

2.1 Dataset

We analyzed records found in the Veterans Affairs (VA) Corporate Data Warehouse (CDW) for patients with entries along the Text Integration Utility (TIU) database and confirmed death with the CDC's National Death Index (NDI). At the time of the analysis, records were available between 1/1/2000 and 1/1/2020, and NDI death statistics were available through the end of 2018. In total, 3,989,502 patients had TIU Document records and a confirmed death in the NDI. Patients were subset into suicide death cases and two control groups with non-suicide-related death.

Cases of suicide death were defined as patients with ICD10 codes X60-X84 and Y87 as their underlying cause of death. Of the remaining patients with other underlying causes of death, two control groups were formed under the condition of having a previous history of diagnosed mental illness or not. Diagnosis codes for mental illness included ICD9 (290.X, 293.X, 295.X, 296.X, 297.X, 298.X, 300.X, 301.X, 307.X, 308.X, 309.X, or 311.X) and ICD10 (F20, F21, F22, F23, F24, F25, F29, F30, F31, F32, F33, F34, F41, F43, F60 or F63) codes. Diagnosis of suicide ideation or attempt were also included.

Controls were randomly down sampled from their corresponding subset to remain proportional to the total number of completed suicide cases. Random sampling was adjusted by median date of birth to ensure that the control groups remained congruent along age distribution with the suicide cases. A total 130,782 patients (n=43,594 per group) with a corpus of 47,535,682 documents were used in this analysis. Table 1 describes socio-demographic characteristics of case and control groups.

2.1.1 Baseline Document Retrieval Using S-EHR

To observe the contribution of NLP to the detection of LE indicators, a baseline for the prevalence of each LE along S-EHR data was measured from inpatient diagnosis codes, outpatient diagnosis codes, outpatient VHA service Stopcodes, and health factor tables. The occurrence of these structured variables was measured over cases and control groups. Table 6 shows descriptions of each LE and definitions along S-EHR, and Table 1 shows the prevalence of the LE along patients. Table 2 reports the number of documents retrieved by S-EHR.

2.2 Concept Extraction Using Natural Language Processing

We developed a pipeline (Figure 1) that compiles concepts for 9 LE, performs named-entity recognition using pattern matching over VHA documents, and discriminates false-positive annotations using clinical text analysis tools. Methods were explored to expand lexicons for these LE, measure the performance of LE extraction between unstructured and structured methods, and measure the impact of NLP-derived variables at discriminating high-risk suicide patients. We primarily focus on the development of domain-specific lexicons and delegate text analysis to the Clinical Event Recognizer (CLEVER), an open-source hybrid framework that pairs statistical and rule-based components for information extraction (Tamang, 2016).

2.2.1 Constructing Domain Specific Lexicons

Knowledge-Based Lexicon The baseline lexicons for the 9 LE were gathered using various sources such as the UMLS, content analysis by subject matter experts (SME) at the VA and the Gravity Project (Bodenreider, 2004; “The Gravity Project”, 2021). Table 2 of the supplementary materials (SM) provides a comprehensive list of concepts. Named-entity recognition may indicate the presence of the risk factor but may not produce exact evidence of the LE for a patient of interest.

Data-Driven Lexicon Knowledge-based lexicons alone may be insufficient at capturing LE indicators specific to EHR data (Tamang et al., 2017). VHA healthcare prose and vocabulary vary heavily across providers and subject matter domains. In addition, text may include jargon, misspellings, and abbreviations particular to healthcare providers. To improve the sensitivity of LE extraction we explore using contextual word representations trained on TIUDocuments to find statistically similar words and phrases to terms found in the knowledge-based lexicon and validated by SME.

We applied Word2Vec by Mikolov et. al (2013a) to a sample of 711,457 documents from 3,000 random patients across case and control groups. The Word2Vec language model produces an embedding where proximity indicates statistical similarity. To expand the knowledge-based lexicon, we perform a nearest-neighbor search using the Word2Vec embedding and apply cosine similarity to rank terms found in the documents by proximity to the knowledge-based lexicon. The Word2Vec default output of the top 30 nearest-neighbors for each term in the knowledge-based lexicon were gathered and those that were misaligned with the definition of the LE were not included in the final data-driven lexicon. SM Table 1 provides an example query for two LE. SME reviewed the final lexicons.

Parameterization for Word2Vec was defined according to heuristics from Mikolov et al. (2013b) and Pennington et al. (2014). A continuous bag-of-words architecture using negative instance sampling of 0.001 with a context window of 5, a learning rate of 0.025, and an embedding dimensionality of 400 was employed. An additional pre-processing step called Word2Phrase was used to build n-grams or phrases. To include n-grams found in the corpus, the dataset was lower-cased, non-alphanumeric characters were removed, and pre-processed through Word2Phrase for two iterations before training.

2.2.2 Annotation Using Text Analysis

Clinical text analysis was performed over the corpus using CLEVER with both the knowledge-based and data-driven lexicons. The CLEVER framework consists of (1) bootstrapping a set of “seed” terms using Word2Vec embeddings to develop a terminology specific to a corpus, (2) using the terminology to tag relevant clinical concepts within patients notes, (3) merging text-based extractions with relevant structured data and (4) applying heuristics to “weakly” labeled

mentions based on their context. CLEVER has been validated for various applications (Tamang et al., 2017; Ling et al., 2019; Gianfrancesco et al., 2019).

2.3 Validating Concept Extraction and Document Retrieval Performance

A manual review is necessary to measure the performance of the document retrieval method. For each LE, 50 random documents were sampled from the union of those retrieved by both S-EHR and NLP. Another 50 random documents were sampled from those documents exclusive to either S-EHR or NLP. Combined, 900 documents were reviewed, 100 per LE.

After sampling documents for validation, a group of reviewers (n=3) read through each document and assessed whether sufficient evidence was present to confirm the mention of the LE. Cohen's Kappa statistic was used to assess inter-rater agreement. It accounts for the probability of chance agreement between raters (Berry and Mielke, 1988) and represents the extent to which the labels are accurate representations of the observed variables (McHugh, 2012). Table 3 reports the inter-rater agreement between reviewers across LE categories.

Labels assigned by reviewers were considered ground truth and used to measure the recall, positive predictive value (PPV) and F1-score of retrieval by S-EHR, knowledge-based annotation, and data-driven annotation. Although these metrics are useful for interpreting the relative improvement in performance between S-EHR and NLP retrieval, they do not provide insight into the overall sensitivity of methods along a complete patient corpus. Table 3 reports the average recall, PPV, and F1-score between reviewer labeling. SM Figure 6 provides additional confusion matrices for each extraction method.

2.4 Measuring Impact of NLP Variables on Suicide Mortality

An implementation of RV was developed and used to observe the impact of NLP-derived variables on predicted suicide risk. One hundred eighty-eight baseline RV variables were gathered along a coarse-grained time period of 7.5 years before outcomes to improve statistics for populated variables. The span of the selected time period with log scaled ranges ensures a more complete snapshot of predictor variables along patient timelines and improves the statistical significance of the model given the high sparsity of the structured variables across time. The time of prediction was defined to be 45 days prior to the death of patients as indexed by the NDI to ensure that surrogate signals related to the outcome variable are not included along predictor variables.

Each predictor was encoded as a presence/absence variable along 8 temporal bins of variable length prior to the time of prediction. Two independent sets of LE predictors were encoded from indicators retrieved by S-EHR and data-driven annotation respectively. NLP variables were separated from S-EHR variables to improve interpretability of the additive contribution of NLP-derived variables to those encoded from S-EHR.

Logistic regression using a generalized linear model with elastic net penalty was used to model the effect of each suicide predictor with respect to mortality outcomes. Two models were constructed for discrimination of suicide cases from each control group. For each model, patient data was divided into training and testing sets along an equal sampling by median date of birth. Model fit was assessed using AUC on the testing set of patients (n=43,594). Figure 3 reports the model coefficients over S-EHR and NLP-derived variables for the 9 LE.

Outreach is done for the top 0.1% of predictions by RV probability, considered to be at imminent risk for suicide. We use RV risk-stratification to observe the effect of the NLP-derived variables on the discrimination of high-risk patients. Along both training and testing sets (n=87,188 for each model), the prevalence of LE indicators over patients were measured across the top 0.1%, 0.5%, 1%, 5%, 10%, 25%, 50% and 75% of predicted probabilities, with and without NLP-derived variables. Tables 4 and 5 report both prevalence measures across the 9 LE for each mortality model respectively.

A glossary for important terminology used in our methodology can be found at <https://github.com/CrivelliLab/Glossary/blob/main/Natural%20Language%20Processing>.

3 Results

Figure 2 reports the average co-occurring LE a patient experiences as time of death or outcome approaches. We show that suicide cases had on average, a higher rate of LE over time when compared to control patients with no previous history of diagnosed mental illness. Control patients with a previous history of mental illness were more difficult to distinguish from the cases. More importantly, the prevalence of co-occurring LE extracted by NLP from unstructured data was higher than that from structured data. Our study found that structured data points for these LE are rare events with low prevalence across the 7.5 years before death.

Table 1 reports the characteristics of the study cohort including the demographics and LE prevalence for cases and controls. Across the entire cohort, only 3.92% of patients had been diagnosed with suicide ideation and 3.04% had a diagnosed suicide attempt. Along S-EHR, housing instability was the most prominent LE experienced by patients, followed by drug and alcohol detoxification and job instability. Food insecurity and access to lethal means were sparse over S-EHR with less than 50 patients having some indication of these LE. Patients with completed suicides had higher rates of drug and alcohol detoxification, job instability, justice, and MST than both control groups. Patients with a previous history of diagnosed mental health had greater rates of housing instability and social isolation than patients who completed suicide.

Table 2 reports the number of TIUDocuments retrieved using the three methods explored in this analysis. In total, 1.51% of the study's corpus was retrieved using S-EHR, 2.87% with a knowledge-based annotation search, and 5.66% with the data-driven annotation search. Overall, a greater quantity of documents was retrieved using either NLP approach for these LE. Aside from access to lethal means and food insecurity, which were extremely sparse over S-EHR, relationship issues had the highest increase in prevalence along patients in the study (229.94 fold increase) followed by MST (54.00 fold increase), justice (29.64 fold increase) and reduced social connection (12.01 fold increase). Even so, an overall higher rate of return does not necessarily imply a higher ability to detect indicators.

Table 3 reports results from the reviewer validation. Reviewer agreement over the labeling of the 9 LE ranged from substantial agreement to near-perfect agreement. While still considered to be substantially in agreement, detoxification had the lowest score followed by reduced social connection and relationship issues. Over each validation set, the NLP method using the data-driven lexicon had the highest rate of recall when compared to S-EHR and knowledge-based annotation. On the other hand, S-EHR consistently had the highest PPV across categories although the recall of this method trailed behind NLP approaches. When comparing the methods along the F1-score, the NLP method using the data-driven lexicon outperformed the

other methods even with some loss in PPV. For the two mortality models using LE predictors, the AUC across each test set were 0.891 and 0.911 when discriminating cases from controls with and without previously diagnosed mental illness respectively.

Figure 3 shows the LE variable coefficients from the logistic regression mortality models. Comparing the magnitude of the coefficients, we find that NLP-derived variables were more predictive as the time of death approaches than S-EHR variables. Specifically, NLP-derived variables access to means, relationships, job instability, and justice were predictive for discriminating suicide cases from controls without previously diagnosed mental illness. NLP variables were less predictive for discriminating suicide cases from controls with previously diagnosed mental illness. This is unsurprising given that the cases and controls with previously diagnosed mental illness show similar behavior in terms of incidence of LE as illustrated in Figure 2.

Tables 4 and 5 report the prevalence of LE indicators across the tiers of predicted probability from the two mortality models with and without NLP variables. When discriminating cases from controls with no diagnosed mental illness, the introduction of NLP variables increased the percentage of patients who ever indicated positive for a LE (composed from S-EHR and NLP) along the top 0.1% to 1% of predicted probabilities. While not having a significant impact on the AUC of the model, the inclusion of NLP-derived variables increased the likelihood of selecting patients with LE indicators. This is particularly significant for access to lethal means, relationships, justice, housing instability, and food insecurity, for which NLP greatly increased the percentage of cases with these LE in the top 0.1% tier. This was not true for cases vs controls with previous history of diagnosed mental illness for which the concentration of LE across the high-risk tier of predicted probability either remained the same or decreased except for minor increases in the top 0.1% of predictions for justice, job instability, and relationship issues.

Additional information regarding the number of patients extracted per LE and co-occurring LE with shortened patient timelines are provided in SM Figures 1-5. Example runtime analysis is provided in SM Figure 7.

4 Discussion

Suicide is a complex problem where predisposition to suicide risk factors needs to be studied in the context of stressful LE over time. In this study, we focused on the extraction of LE indicators from unstructured data using NLP and demonstrated an increase in detecting indicators in the months prior to Veteran suicides. Adding NLP-derived variables to RV increased the concentration of LE across the top percentiles of predicted risk when discriminating between completed suicides and deaths of patients with no previous history of diagnosed mental health. We demonstrated that named-entity recognition and text analysis can be used to increase the recall of documents with LE when compared to document retrieval along S-EHR. These methods may be applicable outside the context of the VA and benefit the identification of these indicators for institutions that have not implemented related health factors surveys. Nevertheless, more work should be done to further improve the LE definitions along available VHA data, add additional terms to ongoing lexicons, and improve the performance of NLP retrieval with additional semantic analysis.

4.1 Limitations and Future Work

Some LE did not show improved detection using the current NLP configuration. For instance, expanding terminology for MST did not produce any meaningful contributions. This can be attributed to the strict definition of MST, textual indicators for MST being heavily structured through boilerplate questionnaires, and a low rate of free text describing MST in the corpus sample used when training embedding methods. Detecting drug and alcohol detoxification was shown to be a non-trivial task even for reviewers across the validation set. Detoxification had the lowest inter-rater agreement of the LE, and post-validation discussion with clinicians focused on the difficulty of discriminating periods of detoxification from other events common for Veterans struggling with substance abuse. The current lexicon expansion procedure is heavily dependent on manual selection of related terms by SME. Future work would benefit from defining heuristics for selecting related terms and for verifying alignment between concepts and terms.

While this analysis is considered large-scale, more work is required to scale methods to the complete VHA cohort of 22 million Veterans and integrate all annotations to operation. A major drawback to using larger-scale data for NLP is the resources required for manually validating a statistically significant sample of annotations. To get an accurate measure of the overall prevalence of a LE in a corpus, the number of documents that must be reviewed by SME would need to be some orders of magnitude greater than in this study. Due to resource constraints, we strategically sampled documents to provide a measure of relative improvement in LE detection between structured and unstructured approaches. We show NLP is useful in increasing the sensitivity of LE variables compared to structured variables alone, but the true prevalence of LE is not reported by this analysis.

The inclusion of NLP-variables results in a reordering of patients by risk where those ranked highest also have a high likelihood of having one or more LE in their medical history. The most recent study by McCarthy et al. (2021) showed that although RV can help identify patients at high risk of suicide, and reduce mental health admissions, emergency department visits, and suicide attempts, these patients remain at high risk even 6 months after they were identified. It is unknown whether outreach services for patients selected along this risk distribution would decrease their likelihood of suicide. Patients identified with and without these variables should be studied to assess the impact of outreach programs. Furthermore, the analysis does not take into consideration the compounded effect of the LE as a predictor and only considers the contribution of each LE to suicide death independently in the linear model.

Finally, although our study examines a limited list of LE, it sets the foundation for future analysis of other LE.

4.2 Importance

This study is an initial but necessary step that has both clinical and research implications for the use of NLP in the VHA data infrastructure and its operational models. Methods and tools were developed to scale to the large quantity of textual data available within the VA, at a magnitude higher than previous research. Employing domain-specific lexicons, we demonstrated that named-entity recognition and text analysis was sufficient to retrieve documents of interest, and results increased the identification of LE among those patients at the top 0.1%, 0.5% and 1% of predicted risk. Given the high percentage of these patients going through LE, it is important to develop comprehensive programs that treat them and help them overcome their LE-related problems as well as predictive models that can anticipate these LE and the compounded effect that they may create (Nordenberg, 2022).

The inclusion of LE variables may help identify novel sub-populations of Veterans who are ranked low in the current RV model but may be more positively affected by outreach or

proactive services. As previous studies have shown, the early detection of these events and prevention services can reduce medical costs and most importantly, save lives. These are important future directions in continuing to use NLP to prevent Veterans' suicide.

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Figure 1: Natural language processing pipeline for identifying suicide-related LE in VA medical documents.

Figure 2: Average number of LE identified prior to death using knowledge-based lexicon versus data-driven lexicons. Average number of LE measured along structured EHR variables are plotted as dotted lines for comparison.

(a) Suicide cases and controls with no history of mental health diagnosis

(b) Suicide cases and controls with history of mental health diagnosis

Figure 3: LE variable coefficients from logistic regression mortality models. Each bar represents cumulative impact on predicted risk for presence of variable along 8 time bins. Height of the bars represent predictive (positive coefficient) or protective impact on predicted risk (negative coefficient). Shade of sections within the bars indicates proximity to outcome date (darker indicating closer proximity than lighter). Width of the bars represents the overall prevalence of the variable across patients. section indicates proximity to outcome date. Width of bar represents the overall prevalence of variable across patients.

Table 1: Socio-demographic characteristics, structured EHR variables, and TIU Document counts among outcome groups. * Definitions for LE medical codes and health factors surveys in Table 6.

		Overall(n=130,782)	Cases (n=43,594)	Controls w MH(n=43,594)	Controls w/o MH(n=43,594)
Sex	Male	127,758 (97.69%)	42,338 (97.12%)	42,469 (97.42%)	42,951 (98.53%)
	Female	3,024 (2.31%)	1,256 (2.88%)	1,125 (2.58%)	643 (1.47%)
Race	White	75,999 (58.11%)	26,480 (60.74%)	27,037 (62.02%)	22,482 (51.57%)
	Black/African American	8,707 (6.66%)	1,744 (4.00%)	4,329 (9.93%)	2,634 (6.04%)
	Other Racial Identity	1,739 (1.33%)	637 (1.46%)	622 (1.43%)	480 (1.10%)
	Unknown	44,337 (33.90%)	14,733 (33.80%)	11,606 (26.62%)	17,998 (39.05%)
Hispanic Ethnicity	No	86,163 (65.88%)	28,844 (66.17%)	31,519 (72.30%)	25,800 (59.18%)
	Yes	3,384 (2.59%)	1,149 (2.64%)	1,466 (3.37%)	769 (1.76%)
	Unknown	41,235 (31.53%)	13,601 (31.20%)	10,609 (24.34%)	17,025 (39.05%)
Marital Status	Married	66,608 (50.93%)	18,088 (41.49%)	22,086 (50.66%)	26,434 (59.18%)
	Widowed	15,821 (12.10%)	3,177 (7.29%)	6,137 (14.08%)	6,507 (14.93%)
	Divorced	28,366 (21.69%)	12,513 (28.70%)	9,508 (21.81%)	6,345 (14.55%)
	Separated	3,606 (2.76%)	1,507 (3.46%)	1,353 (3.10%)	746 (1.71%)
	Single/Never Married	13,331 (10.19%)	7,077 (16.23%)	3,680 (8.44%)	2,574 (5.90%)
	Unknown	3,050 (2.33%)	1,232 (2.82%)	830 (1.90%)	989 (2.26%)
Age at Death	< 20	5 (<0.01%)	4 (<0.01%)	0 (0.00%)	1 (<0.01%)
	20-29	2,334 (1.78%)	2,238 (5.13%)	69 (0.16%)	27 (0.62%)
	30-39	3,951 (3.02%)	3,610 (8.28%)	237 (0.54%)	104 (0.24%)
	40-49	6,671 (5.10%)	5,196 (11.92%)	1,000 (2.29%)	475 (1.09%)
	50-59	15,385 (11.76%)	8,572 (19.66%)	4,582 (10.51%)	2,231 (5.12%)
	60-69	24,638 (18.84%)	9,227 (21.17%)	9,385 (21.53%)	6,026 (13.82%)
	70-79	31,046 (23.74%)	7,903 (18.13%)	10,779 (24.73%)	12,364 (28.36%)
	80-89	36,721 (28.08%)	5,917 (13.57%)	13,816 (31.69%)	16,988 (38.97%)
	> 89	10,031 (7.67%)	927 (2.13%)	3,726 (8.55%)	5,378 (12.34%)
Diagnosis	Suicide Ideation	5,121 (3.92%)	3,680 (8.44%)	1,441 (3.31%)	0 (0.00%)
	Suicide Attempt	3,981 (3.04%)	2,837 (6.51%)	1,144 (2.62%)	0 (0.00%)
LE*	Food Insecurity	41 (0.03%)	13 (0.02%)	20 (0.05%)	8 (0.02%)
	Housing Instability	19,102 (14.61%)	6,330 (14.52%)	9,946 (22.82%)	2,826 (6.48%)
	Job Instability	6,599 (5.05%)	3,735 (8.57%)	2,503 (5.74%)	361 (0.83%)
	Justice	1,079 (0.83%)	707 (1.62%)	331 (0.76%)	41 (0.09%)
	Social Connection	4,929 (3.77%)	1,291 (2.96%)	2,633 (6.04%)	1,005 (2.31%)
	Social Connection Relationships	229 (0.18%)	175 (0.40%)	48 (0.11%)	6 (0.01%)
	Military Sexual Trauma	1,670 (1.28%)	893 (2.05%)	618 (1.42%)	159 (0.36%)
	Detox	14,671 (11.28%)	6,799 (15.60%)	5,096 (11.69%)	2,776 (6.34%)
	Access to Lethal Means	40 (0.03%)	20 (0.05%)	19 (0.04%)	1 (<0.01%)
TIU Documents		47,535,682	12,151,160	27,485,549	7,898,973

Table 2: Number of TIUDocuments selected by LE category across outcome groups. For knowledge-based and data driven search criteria, number of unique patients is reported with document count.

		Structured EHR Linked	Knowledge-Based Search	Data-Driven Search
TIUDocuments	Overall (n=130,782)	716,155	1,363,179	2,690,430
	Cases (n=43,594)	331,233	588,750	1,153,032
	Controls w MH (n=43,594)	353,745	649,436	1,306,426
	Controls w/o MH (n=43,594)	31,177	124,993	230,972
LE	Group			
Housing Instability	Overall	232,848	604,428 (n=65,258)	665,860 (n=67,773)
	Cases	90,370	241,768 (n=23,039)	268,633 (n=23,972)
	Controls w MH	130,192	306,604 (n=26,239)	337,454 (n=27,309)
	Controls w/o MH	12,286	56,056 (n=15,980)	59,773 (n=16,492)
Job Insecurity	Overall	90,241	283,804 (n=46,925)	492,827 (n=58,141)
	Cases	50,113	144,157 (n=19,496)	243,404 (n=22,974)
	Controls w MH	38,128	124,397 (n=20,275)	222,797 (n=25,356)
	Controls w/o MH	2,000	15,250 (n=7,154)	26,626 (n=9,811)
Justice	Overall	6,088	97,742 (n=21,751)	198,668 (n=31,986)
	Cases	4,518	44,837 (n=9,694)	100,038 (n=14,059)
	Controls w MH	1,452	47,430 (n=9,909)	89,275 (n=14,487)
	Controls w/o MH	118	5,475 (n=2,148)	9,355 (n=3,440)
Social Connection	Overall	24,665	142,625 (n=37,868)	649,913 (n=59,195)
	Cases	5,153	62,663 (n=15,158)	292,747 (n=26,564)
	Controls w MH	15,847	67,420 (n=16,786)	308,813 (n=29,095)
	Controls w/o MH	3,665	12,542 (n=5,924)	48,353 (n=13,526)
Social Connection Relationships	Overall	1,153	80,171 (n=27,378)	497,218 (n=52,656)
	Cases	912	33,834 (n=11,075)	222,374 (n=24,939)
	Controls w MH	217	35,835 (n=11,378)	231,964 (n=26,352)
	Controls w/o MH	24	10,502 (n=4,925)	42,880 (n=1,365)
Detox	Overall	379,928	314,196 (n=25,810)	994,215 (n=56,195)
	Cases	190,556	156,647 (n=12,185)	458,466 (n=21,989)
	Controls w MH	176,026	146,884 (n=10,849)	482,651 (n=24,000)
	Controls w/o MH	13,346	10,665 (n=2,776)	53,098 (n=10,206)
Military Sexual Trauma	Overall	6,659	155,705 (n=90,180)	155,705 (n=90,180)
	Cases	3,930	60,093 (n=29,955)	60,093 (n=29,955)
	Controls w MH	2,434	61,635 (n=32,724)	61,635 (n=32,724)
	Controls w/o MH	295	33,977 (n=27,501)	33,977 (n=27,501)
Access to Lethal Means	Overall	104	5,639 (n=3,018)	282,573 (n=54,806)
	Cases	24	3,628 (n=1,945)	132,678 (n=20,468)
	Controls w MH	79	1,939 (n=1,024)	124,150 (n=24,447)
	Controls w/o MH	1	72 (n=49)	25,745 (n=9,891)
Food Insecurity	Overall	78	527 (n=371)	22,671 (n=9,991)
	Cases	25	110 (n=80)	8,460 (n=3,715)
	Controls w MH	39	357 (n=247)	12,334 (n=5,131)
	Controls w/o MH	14	60 (n=44)	1,877 (n=1,145)

Table 3: Performance comparison of document retrieval methods over manually validated documents (n=100 per event). Validation sets were sampled over retrieved documents between structured and text-based methods to observe relative improvement. Validation was conducted between three independent reviewers and agreement between labels was measured using Cohen's Kappa. * Data-driven method did not expand knowledge-based set. ** Structured variables are sparse for these LE.

LE	n	Rater Agreement Cohen's Kappa	(95% CI $\pm$)	Method	Recall	(95% CI $\pm$)	PPV	(95% CI $\pm$)	F1-Score	(95% CI $\pm$)
Housing Instability	100	0.869	0.066	Structured	0.706	0.089	0.831	0.074	0.763	0.083
				Knowledge-Based	0.929	0.051	0.731	0.087	0.817	0.076
				Data-Driven	0.967	0.035	0.736	0.086	0.835	0.073
Job Instability	100	0.829	0.074	Structured	0.617	0.095	0.949	0.043	0.746	0.085
				Knowledge-Based	0.366	0.094	0.792	0.079	0.500	0.098
				Data-Driven	0.987	0.021	0.810	0.077	0.888	0.062
Justice	100	0.950	0.043	Structured	0.647	0.094	0.974	0.031	0.778	0.082
				Knowledge-Based	0.340	0.092	0.684	0.091	0.455	0.098
				Data-Driven	0.987	0.022	0.789	0.080	0.877	0.064
Social Connection	100	0.766	0.073	Structured	0.524	0.098	0.497	0.098	0.510	0.098
				Knowledge-Based	0.221	0.081	0.508	0.097	0.308	0.090
				Data-Driven	1.000	0.000	0.488	0.098	0.656	0.093
Social Connection Relationships	100	0.778	0.081	Structured	0.670	0.092	0.937	0.048	0.777	0.082
				Knowledge-Based	0.210	0.080	0.789	0.080	0.330	0.092
				Data-Driven	1.000	0.000	0.727	0.087	0.835	0.073
Detox	100	0.656	0.093	Structured	0.714	0.089	0.754	0.084	0.733	0.087
				Knowledge-Based	0.300	0.090	0.716	0.088	0.422	0.097
				Data-Driven	0.932	0.051	0.674	0.092	0.780	0.081
Military Sexual Trauma*	100	0.959	0.039	Structured	0.896	0.060	0.980	0.027	0.936	0.048
				Knowledge-Based	1.000	0.000	0.547	0.098	0.707	0.089
				Data-Driven	-	-	-	-	-	-
Access To Lethal Means**	100	0.919	0.053	Structured	0.632	0.095	0.947	0.044	0.758	0.084
				Knowledge-Based	0.020	0.026	1.000	0.000	0.035	0.036
				Data-Driven	1.00	0.000	0.580	0.097	0.731	0.087
Food Insecurity**	100	0.859	0.070	Structured	0.000	0.000	0.000	0.000	0.000	0.000
				Knowledge-Based	0.000	0.000	0.000	0.000	0.000	0.000
				Data-Driven	1.000	0.000	0.587	0.097	0.739	0.086

Table 4: Prevalence of LE across tiers of predicted probability from logistic regression discriminating suicide cases from controls with no history of mental health diagnosis (n=87,188). Predicted risk was measured using baseline ReachVet variables and structured LE variables. NLP derived variables were introduced to observe changes in LE concentration along high risk patients.

Tier of predicted probability, %	Housing - Structured EHR	Instability; w/ NLP	Job - Structured EHR	Instability; w/ NLP	Justice; Structured EHR	w/ NLP	Social - Structured EHR	Connection; w/ NLP	Social Connection - Structured EHR	Relationship; w/ NLP
	% patients	% patients	% patients	% patients	% patients	% patients	% patients	% patients	% patients	% patients
0.1	86.36	97.73	93.18	94.32	68.18	78.41	95.45	96.59	90.91	95.45
0.5	88.76	94.04	94.04	95.64	71.10	77.75	96.56	97.94	92.43	95.64
1	90.82	94.14	94.26	95.98	73.59	77.50	96.79	97.59	92.54	94.95
5	91.07	91.44	94.03	94.33	74.12	74.88	96.35	96.72	92.28	92.84
10	85.84	86.11	88.10	88.45	64.14	64.68	91.82	92.17	87.13	87.47
25	70.05	70.73	68.97	70.05	43.68	44.71	75.21	76.40	70.21	71.32
50	49.60	50.83	46.46	47.70	26.93	27.50	52.65	54.43	48.88	50.51
75	39.66	40.06	34.99	35.39	19.25	19.48	40.93	41.54	37.90	38.44
100	42.29	42.29	32.29	32.29	16.23	16.23	38.89	38.89	35.74	35.74

Tier of predicted probability, %	Detox; Structured EHR	w/ NLP	Military - Structured EHR	Sexual Trauma; w/ NLP	Access To - Structured EHR	Lethal Means; w/ NLP	Food - Structured EHR	Insecurity; w/ NLP	Completed - Structured EHR	Suicides; w/ NLP
	% patients	% patients	% patients	% patients	% patients	% patients	% patients	% patients	% patients	% patients
0.1	90.91	95.45	64.77	72.73	88.64	92.05	25.00	39.77	100.00	100.00
0.5	90.60	94.04	63.53	71.33	89.68	94.50	20.87	29.13	100.00	100.00
1	91.04	94.49	67.16	72.22	92.31	94.14	23.77	27.67	100.00	100.00
5	91.14	91.32	70.54	70.61	90.10	90.42	25.76	25.83	100.00	100.00
10	84.56	84.82	68.19	68.10	80.81	81.10	20.52	20.56	100.00	100.00
25	66.92	67.65	62.11	61.91	59.48	60.24	12.10	12.19	98.31	98.40
50	44.65	45.50	49.51	50.52	38.07	38.81	6.97	7.03	82.06	82.50
75	33.56	33.78	44.90	44.75	28.69	28.93	4.95	4.93	64.72	64.81
100	31.39	31.39	46.04	46.04	27.39	27.39	4.45	4.45	50.00	50.00

Table 5: Prevalence of LE across tiers of predicted probability from logistic regression discriminating suicide cases from controls with history of mental health diagnosis (n=87,188).

Tier of predicted probability, %	Housing - Structured EHR	Instability; w/ NLP	Job - Structured EHR	Instability; w/ NLP	Justice; Structured EHR	w/ NLP	Social - Structured EHR	Connection; w/ NLP	Social Connection - Structured EHR	Relationship; w/ NLP
	% patients	% patients	% patients	% patients	% patients	% patients	% patients	% patients	% patients	% patients
0.1	90.91	90.91	94.32	95.45	75.00	77.27	97.73	97.73	93.18	94.31
0.5	88.07	86.70	93.81	92.20	75.92	74.32	95.64	95.41	91.28	90.83
1	84.63	84.40	88.76	88.42	67.43	67.43	91.40	91.63	86.81	87.50
5	79.63	79.31	78.88	78.51	54.56	54.56	83.46	83.69	79.29	79.77
10	75.12	74.62	72.20	71.69	47.48	47.48	77.34	77.38	72.94	73.08
25	64.20	63.46	59.98	59.54	36.99	36.99	66.23	66.20	62.12	62.15
50	48.42	48.28	45.31	45.24	26.60	26.60	51.64	51.73	47.95	48.08
75	47.98	47.90	43.71	43.60	24.52	24.52	50.64	50.69	46.29	46.35
100	55.20	55.20	48.69	48.69	26.81	26.81	55.92	55.92	50.69	50.69

Tier of predicted probability, %	Detox; Structured EHR	w/ NLP	Military - Structured EHR	Sexual Trauma; w/ NLP	Access To - Structured EHR	Lethal Means; w/ NLP	Food - Structured EHR	Insecurity; w/ NLP	Completed - Structured EHR	Suicides; w/ NLP
	% patients	% patients	% patients	% patients	% patients	% patients	% patients	% patients	% patients	% patients
0.1	93.18	93.18	80.68	78.41	97.73	97.73	23.86	20.45	95.45	95.45
0.5	92.66	90.37	72.02	71.33	90.83	89.22	23.62	18.81	96.79	96.33
1	88.42	87.04	69.04	68.81	84.63	83.95	21.90	18.81	96.56	96.56
5	79.10	77.34	63.74	63.33	72.82	72.06	17.25	15.89	94.06	94.33
10	72.52	71.05	62.89	62.44	64.69	63.75	14.46	13.10	93.35	93.49
25	59.39	58.16	59.03	58.80	51.15	50.40	10.62	9.78	91.78	91.89
50	43.62	43.13	48.20	48.45	37.02	36.74	7.02	6.71	82.29	82.23
75	41.53	41.19	49.52	49.41	36.38	36.23	6.42	6.24	65.39	65.42
100	46.22	46.22	49.79	49.79	42.45	42.45	8.14	8.14	50.00	50.00

Table 6: Definitions of suicide-related LE across structured data sources.

LE Description
<p>Housing Instability</p> <p>Housing Instability is part of the Economic Stability Determinant Area within the “place-based” organizing framework of the Healthy People 2020 Approach to Social Determinants of Health. Terms in this domain were provided by SIREN’s Compendium of medical terminology codes for social risk factors (Arons et al., 2018). Terms in this domain consist of various acronyms, VA programs, and adjectives and verbs describing the patients current living situation.</p> <p>ICD9: V60.X; ICD10: Z59.0, Z59.1, Z59.8, Z59.9; VA StopCode: 501, 504, 507, 508, 511, 522, 528, 529, 530, 555, 556, 590, 591, 592, 725; Health Factor Survey Regex (HealthFactorCategory,HealthFactorType): r"CURRENT LIVING\HOMELESSNESS", r"LIVES IN (INSTITUTION\MOTEL\SHELTER)\LIVES WITH FRIEND\LIVES ON STREET\POSITIVE\^REFERRED"</p>
<p>Job Instability</p> <p>Employment is part of the Economic Stability Determinant Area within the “place-based” organizing framework of the Healthy People 2020 Approach to Social Determinants of Health. Terms in this domain were identified via SIREN’s Compendium of medical terminology codes for social risk factors (Arons et al., 2018). Terms in this domain consist of varying ways to describe current unemployment status and financial difficulties, with the addition of select VA programs. Social security and disability benefits terms are not included.</p> <p>ICD9: V62.0, V62.1, V62.2; ICD10: Z56.X; VA StopCode: 555, 556, 568, 999, 575, 535, 536, 574, 206; Health Factor Survey Regex (HealthFactorCategory,HealthFactorType): r"COMPENSATED WORK THERAPY\CWT",r"CWT\PATIENT"</p>
<p>Justice</p> <p>Incarceration is part of the Social and Community Context Determinant Area within the “place-based” organizing framework of the Healthy People 2020 Approach to Social Determinants of Health. Terms in this domain were identified via SIREN’s Compendium of medical terminology codes for social risk factors (Arons et al., 2018). This domain includes terms related to involvement with the criminal justice system and is focused on incarceration.</p> <p>ICD9: V62.5; ICD10: Z65.0, Z65.1, Z65.2, Z65.3, Z65.4, Z65.5; VA StopCode: 591, 592;</p>
<p>Social Connection</p> <p>Social Cohesion is part of the Social and Community Context Determinant Area within the “place-based” organizing framework of the Healthy People 2020 Approach to Social Determinants of Health. Terms in this domain were identified via SIREN’s Compendium of medical terminology codes for social risk factors (Arons et al., 2018). Term selection is focused on various adjectives of social isolation and limited social support.</p> <p>ICD9: V62.4, V61.1, V61.03; ICD10: Z60.X, Z63.1, Z63.3, Z63.4, Z63.6, Z63.7, Z63.8, Z63.9; Health Factor Survey Regex (HealthFactorCategory,HealthFactorType): r"NEGLECT\ISSUES INVOLVING \FAMILY\PTSD AVOIDANCE\PTSD DETACHMENT\SOCIAL ISOLATION\SOCIAL \ABUSE", r"HISTORY\ACTIVE\YES\POS\TIVE\)\ABUSE\NEGLECT\^DC\^ET\DIFFICULTY\EMOTIONAL CONCERNS";</p>
<p>Social Connection Relationship</p> <p>Social Cohesion is part of the Social and Community Context Determinant Area within the “place-based” organizing framework of the Healthy People 2020 Approach to Social Determinants of Health. Terms in this domain were identified via SIREN’s Compendium of medical terminology codes for social risk factors (Arons et al., 2018). This domain includes terms specifically focused on relationship problems, particularly around current martial status and issues.</p> <p>ICD9: V61.1, V61.03; ICD10: Z63.0, Z63.5; Health Factor Survey Regex (HealthFactorCategory,HealthFactorType): r"DOMESTIC VIOLENCE\HOME VIOLENCE\PARTNER ABUSE", r"YES\POS\TIVE\)\OFTEN\FREQUENT\SOMETIMES\^CURRENT PARTNER\EXPARTNER";</p>
<p>Detox</p> <p>This domain includes terms related to detoxification from substances including alcohol. Current untreated substance abuse was not included in definition. Many terms are inclusive of VA programs and their acronyms.</p> <p>ICD9: 291.0, 292.0; ICD10: F1[12345689].[129]3 ,Z71.5; VA StopCode: 513, 514, 519, 523, 545, 560, 706, 707, 708, 721, 722, 723, 724; Health Factor Survey Regex (HealthFactorCategory,HealthFactorType): r"ALCOHOL ASSESSMENT INPT \SW\)\ALCOHOL COUNSELING\ALCOHOL WITHDRAWAL PROTOCOL \INPATIENT SUBSTANCE ABUSE\RN CP ALCOHOL WITHDRAWAL DELIRIUM\SUBSTANCE ABUSE ACUTE CARE\SUBSTANCE ABUSE MEDICATIONS",</p>
<p>Military Sexual Trauma</p> <p>This domain includes terms related to military sexual trauma. Generalized sexual and physical trauma terms are not included.</p> <p>VA StopCode: 524; Health Factor Survey Regex (HealthFactorCategory,HealthFactorType): r"MSTMILITARY SEXUAL TRAUMA\MST \RELATED\)\MST CATEGORY\MST CATEGORY", r"MSTIYESIREQUESTS\POS\TIVE\)"</p>
<p>Access To Lethal Means</p> <p>Our current selection of terms is informed by the report of the Action Alliance titled Lethal Means And Suicide Prevention: A Guide for Community And Industry Leaders (National Action Alliance, 2020). Lethal means are objects or actions that may be used to carry out a suicide. This domain includes terms related to nouns defined as lethal means.</p> <p>Health Factor Survey Regex (HealthFactorCategory,HealthFactorType): r"CATEGORY: FIREARMS SAFETY\FIREARMS-DEMENTIA",r"FIREARMS ACCESS YES\FIREARMS-YES";</p>
<p>Food Insecurity</p> <p>Food Insecurity is part of the Economic Stability Determinant Area within the “place-based” organizing framework of the Healthy People 2020 Approach to Social Determinants of Health. Terms in this domain are focused on assessment and diagnosis. They are identified via SIREN’s Compendium of medical terminology codes for social risk factors (Arons et al., 2018). Terms in this domain are related to current inability to obtain food and select government programs.</p> <p>ICD10: Z59.4; Health Factor Survey Regex (HealthFactorCategory,HealthFactorType): r"NUTRITION", r"YES\SCREEN\LIMITED ACCESS\NOT ENOUGH MONEY TO BUY FOOD";</p>