Supplemental Online Content

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This supplementary material has been provided by the authors to give readers additional information about their work.

eMethods.

Data sources

As noted in the text, information about predictors in the base model were extracted from three sources:

(i) the Veterans Healthcare Administration (VHA) Corporate Data Warehouse (CDW)[1] (eTable 1), an integrated data system containing information about a wide range of potential predictors, including patient socio-demographics, healthcare encounters in VHA or paid for by VHA, prescriptions written in VHA or paid for by VHA (classified using the VHA Drug Classification System[2]), medical test results, and International Classification of Diseases, Ninth Revision/Tenth Revision Clinical Modification (ICD-9/10-CM) codes for external causes of injury and other factors influencing health status involving social and behavioral determinants of health[3];

(ii) the Veterans Administration (VA) Suicide Prevention Applications Network,[4] an administrative database for suicide behavior tracking in VHA; and

(iii) a *geospatial database* assembled from diverse government sources (eTable 2) about plausible area-level predictors of suicides[5] at the levels of the neighborhood (Census Block Groups and Census Tracts), County, and State of patient residence.

Two other databases were used to assess predictors in addition to those in the base model:

(iv) a *consolidated free text file of VHA clinical notes* for inpatient and outpatient visits up to 12 months before through the date of the hospitalization, including the intake notes for the focal hospitalization[6] used for Natural Language Processing (NLP) analysis; and

(v) the LexisNexis Social Determinants of Health (LN SDoH) database, an aggregation for close to 300 million Americans of public records on household composition, education-occupation, individual and family assets-income, voting records, licenses (including for concealed weapons and explosive devices), and derogatory criminal-financial records (eTable 3) updated as of the month before hospitalization.[7]

Data were missing for small proportions of patients in *(iii)* and *(v)*, but most of these were non-missing in earlier records or, in the case of *(iii)*, in contiguous areas, allowing nearest neighbor imputations. Remaining missing values and inconsistencies were reconciled using rational imputations (eg, a patient classified as female in one record but male in many other records was recoded male) and, in the absence of a basis for rational imputation, by imputing median values.

Predictors

Base model predictors: As noted in the text, four conceptual classes were used to conceptualize the predictors in the Base Super Learner (SL) model. These categories were taken from published studies of risk factors for suicide after psychiatric hospital discharge[8-11] or in the general population.[12-14] These categories were:

(i) psychopathological risk factors, both disorders and medications, including interactions between specific disorders and medications thought to be especially useful in protecting against suicide among patients with these disorders (eg, lithium among patients with bipolar disorder),[15] medical procedures/encounters associated either with increased (eg, substance-related treatment/services)[16] or decreased (eg, certain types of psychotherapy)[17] suicide risk, and history of prior suicidal behaviors[18];

(ii) physical disorders along with medications for those disorders and procedures used to treat those disorders found in previous research to predict suicides[19,20] along with use of medications classified by the Food and Drug Administration (FDA) as increasing risk of suicide (eTable 4). It is noteworthy that the latter are a mix of psychotropic medications and medications for the treatment of physical disorders[21];

(iii) patient-level (from ICD-9/10-CM codes and socio-demographic measures) and geospatial-indicators of social determinants of health (SDoH) known to predict suicide[16, 22-24]; and

(iv) facility-level quality indicators shown in previous research to predict suicides (eg, inpatient staff turnover rate).[8] See Table 3 for a breakdown of the variables from the above classes that had significant univariable associations with 12-month suicide in our training sample defined as 10-fold cross-validated (10F-CV) univariable area under the receiver operating characteristic curve (AUC-ROC) significantly greater than .51 based on .05-level, one-sided tests.

NLP predictors: The first of the two new types of data used in the analysis involve potential predictors extracted from clinical notes using NLP methods based on a document term dictionary developed in an earlier NLP analysis of suicidal behaviors.[25] This rule-based approach took a total of N=1,687 one-, two-, and three-word strings from the dictionary. The notes were then pre-processed using a standard text pipeline by converting all terms to lower case and removing punctuation, numbers, special characters, and blanks. Stop words were not removed. The notes were not lemmatized or stemmed. Notes were consolidated over three different time intervals, in each case retaining the notes for the focal hospitalization and going back either 3, 6, or 12 months prior to hospitalization and then creating a single "super-note" for each patient over each of these three periods. Document term matrices were then created from these super-notes using term frequency x inverse document frequency (tf-idf) weighting.[26] Preliminary analysis of these document terms was carried out using the XGBoost algorithm[27] to predict 12-month suicides in the training sample with 10F-CV used to tune hyperparameters to optimize model discrimination. Model discrimination was found in this preliminary analysis to be higher using 12-month (AUC=.84) than 6-month (AUC=.80) or 3-month (AUC=.82) recall periods. Based on this result, all subsequent NLP analyses used the 12-month recall document term matrix.

In addition to considering the 1,687 strings in this matrix as separate potential predictors, associations among these strings were analyzed with Latent Dirichlet Allocation (LDA) for topic modeling[28,29] to define NLP topics as additional predictors. This was done using the R package *textmineR*.[30] Solutions with 25, 50, and 75 topics were generated and combined into a single dataset with the tf-idf strings as input for the SL NLP model, resulting in a total of 1,837 potential NLP predictors being considered for the model. The 24.1% (N=442) of these potential predictors that had significant univariable associations with 12-month suicide in our training sample were added to the N=1,666 predictors in the Base model to estimate the NLP model.

LN predictors: The LN SDoH database contained an additional N=442 variables, 6.6% (N=29) of which had significant univariable associations with 12-month suicide in our training sample and were added to the N=1,666 predictors in the Base model to estimate the SDoH model.

Combined model predictors: 80% of the total mean absolute SHAP value (see below for a description) in the overall Base model was accounted for by the N=100 predictors with the highest variable specific SHAP values. The comparable number was N=110 predictors in the NLP model. These N=210 predictors were used to estimate the Combined model along with the N=29 individually significant LN predictors, for a total of N=239 potential predictors in the Combined model. However, there was overlap in these predictors across models due to the Base variables emerging among the significant predictors in all models, resulting in the N=239 predictors reducing to N=191 in estimating the Combined model.

Coding of predictors: Categorical predictors were one-hot encoded as 0-1 dummy variables. Ordinal and count variables were standardized to a mean of 0 and variance of 1, with values more than 3 standard deviations above or below mean truncated to 3 or -3.

Analysis methods

Analysis was carried out January-August 2022 using machine learning (ML) methods to predict suicides in the 12 months after hospital discharge using information available at the time of hospital discharge.

Innovations: Numerous reports summarized in recent reviews[31-33] used ML methods to predict suicides from electronic health records.[15,18,34,35] The work we report here used a much more extensive and diverse set of predictors than those earlier studies. It also used innovative approaches to address two problems that frequently occurred in the earlier studies to predict suicidal behaviors[36,37] and to develop other clinical prediction models.[38] First, whereas the great majority of prior studies either used only one classifier or a few classifiers and selected the best one out of the set as the basis for prediction, we used the SL stacked generalization method[39] to pool results across a library of many diverse classifiers. This approach combines predicted outcome scores across all classifiers in a user-specified collection ("ensemble") using a weight generated via one or more holdout samples that is guaranteed in expectation to perform at least as well as the best component classifier according to a pre-specified criterion (in our case, minimizing mean squared error).[40] Consistent with recommendations,[41] we used a diverse set of classifiers in the ensemble to capture nonlinearities and interactions and to reduce risk of misspecification (eTable 5). Second, we used a unique metalearner comparison approach described below to address the twin problems of feature selection and hyperparameter tuning.

Sample segmentation: As noted in the body of the paper, we divided the population into a 70% training sample (discharge dates between January 1, 2010 and August 31, 2012) and a 30% prospective validation sample (discharge dates between September 1, 2012 and December 31, 2013). We then further divided the 70% training sample into random subsamples of 50% for initial model training, 10% for estimating metalearner weights, and a final 10% for calibration. Calibration is of special importance because a case-control sampling scheme was used in model training to address the problem of extreme class imbalance. This was done by including in the analysis sample 100% of cases and a probability sample of 5 times as many controls as cases, assigning a weight of 5 to each case and assigning a weight of 1 to each control, thereby creating a balanced weighted training sample. Predicted log-odds based on the models training in this sample were converted to predicted probabilities using standard methods based on knowledge of true prevalence.[42] These predicted probabilities were then calibrated using logistic or isotonic regression.[43]

The Super Learner stacked generalization approach: Modeling was based on the SL stacked generalization approach, a form of supervised learning in which multiple ways of predicting an outcome variable are evaluated and combined.[44] In this approach, each way of predicting an outcome variable is known as an *estimator* or *learner*, and consists of up to four components:

(i) Estimation algorithm: a prediction method that estimates ("learns") a mapping f(•) from the predictor variables (X) to the outcome variable Y;

(ii) Hyperparameter configuration: the set of tuning settings for an estimation algorithm that must be pre-specified rather than learned from the data;

(iii) Feature selection: Optional identification of a subset of predictors that will be provided to the estimation algorithm to reduce risk of over-fitting rather than using all potential predictors; and

(iv) Feature transformations: optionally any transformations of the original predictor space, such as dimensionality reduction, the addition of interaction terms, imputation of missing values, or the calculation of basic functions. For example, one estimator might be logistic regression with no further customization. Another estimator might be random forest configured to estimate 1,000 trees (a hyperparameter), provided with predictors that have a Pearson correlation coefficient p-value of 0.2 or less (feature selection). Another estimator might be ordinary least squares (OLS) provided with all predictors. Two-way interactions between certain or all pairs of features and squared terms for ordinal and interval features might be added to the predictor list (feature transformations).

Estimators are typically evaluated in the SL approach through k-fold cross-validation, which entails partitioning the analyzed dataset into distinct subsets known as folds. All folds except one are combined into a training set and each estimator is provided with the training set to estimate the mapping f(•) from the predictors (X) to the outcome (Y). The estimator's learned function is then applied to the remaining fold, known as the test set, and evaluated for its accuracy using a pre-specified loss function such as mean-squared error, negative log likelihood loss, or 1 - AUC. Evaluating performance on a held-out test set (or through nested cross-validation) is important in identifying any overfitting. Each fold typically serves as the test set once, and the performance estimates are averaged to determine the CV loss for each estimator.

In the simplest case, the estimator with the lowest CV loss is chosen. This is known as the cross-validation selector and has been proven to perform asymptotically as well as a selection strategy based on understanding the true data distribution (oracle inequality).[45]

The implication is that there is little danger in using CV to choose the best-performing estimator among a set of varied prediction strategies. Rather than only trying our personal favorite method or borrowing a recommendation from the literature, we can empirically validate multiple methods and allow the CV procedure to report which method has been most successful in minimizing our loss function on the dataset at hand. However, choosing a single estimator may leave valuable information unused. As a result, it is sometimes advantageous to combine the predictions of multiple estimators with the aim of improving on the bias- variance tradeoff of any single estimator. SL does this by leveraging the cross-validation approach described above to identify an optimal combination of individual estimators that minimizes the chosen loss function (eg, mean-squared error). This is done by taking the test set data, established when each CV fold is used for evaluation of the estimators, and "stacking" (appending) those test sets into a combined dataset with the same number of observations as the original data. In this stacked dataset, the predicted value of each algorithm becomes a predictor (column), a form of coordinate transformation from the original predictor space, and we call this the "Z" matrix. A metalearner algorithm is then applied to the Z matrix, which learns a function g(•) that maps the test set predictions of each estimator to the outcome variable (Y).

The most common metalearner algorithm is a convex combination of the columns of Z. In that case, it is a simple convex optimization problem to identify the set of non-negative weights summing to 1 that can be applied to the Z matrix to minimize the chosen loss function for predicting Y. This approach is often implemented by using non-negative least squares to estimate non-negative but otherwise unbounded weights and then rescaling those weights to sum to 1. Convex weights are beneficial for several reasons, including that their minimal data-adaptivity reduces the risk of overfitting, they ensure that the ensemble prediction falls within the convex hull of the original estimators' predictions, and they induce sparsity (ie, 1 or more predictors may have a weight of 0 in the ensemble, simplifying the prediction). More complex metalearners might be used instead, such as a random forest or highly adaptive lasso.[46] They risk overfitting to the Z matrix, but if their complexity can be appropriately controlled, their incorporation of interaction terms holds the promise of identifying regions of the estimator space (Z) where certain estimators are more accurate than others. As a result, they may be able to achieve even higher predictive performance than the convex weight metalearner.[47]

Once the metalearner estimator has been trained, each constituent estimator is optionally retrained on the full dataset as the final step. This gives each estimator a slight performance boost by not taking out a rotated test set, as was done during the earlier CV. Additional details on the SL algorithm and best practices are available elsewhere.[48-50]

Hyperparameter tuning: The classifiers in the ensemble varied widely in number of hyperparameters. Hyperparameters can be set at specified values prior to final estimation to increase performance. The typical approach to hyperparameter tuning is to search over the hyperparameter space with CV to find a combination of hyperparameters that optimizes some objective function.[51]

However, this approach selects only one estimator for each classifier, whereas the SL approach allows for the possibility that two or more estimators based on a single classifier might usefully be combined to yield improved prediction compared to any single estimator. This merely requires including multiple specifications of hyperparameter values in the SL ensemble, with the metalearner weights determining whether none, one, or more than one of these specifications has value in improving ensemble performance. eTable 5 lists the hyperparameter values considered for each classifier. We considered each logically possible combination of these values in the ensemble, with initial estimation in the 50% weighted case-control model training sample and metalearner estimation in the 10% metalearner sample.

Variable selection: Initial variable selection was carried out by excluding rare potential predictors (ie, those co-occurring with fewer than 5 12-month suicides in the training sample) and examining univariable 10F-CV AUCs of the others with the outcome in the training sample over a 12-month risk horizon. We eliminated variables that did not have CV AUCs significantly greater than .51 at the .05 level of significance using one-sided tests. We began with 10,181 potential predictors, which was reduced to 2,137 after eliminating rare variables and applying the CV AUC requirement (Table 3).

We explored a range of constraints on the number of predictors separately for each classifier and then combined each of these with the range of hyperparameter profiles described in the previous subsection. Given that the 50% model training sample included N=916 cases (ie, hospitalizations followed within 12 months by a suicide), conventional wisdom suggests that the number of predictors in the model should be no more than 91 to avoid over-fitting.[52] However, empirical support for this one-in-ten rule is weak,[53] leading us to consider a range of values both smaller and larger than this rule-of-thumb for variable selection. Specifically, for each classifier hyperparameter profile we included 6 estimators that used either 15, 30, 50, 100, 250, or all predictors selected based on CV univariable analysis.

The predictors selected when the number of predictors was constrained (ie, between 15 and 250 predictors) were those judged to be most "important". For linear classifiers, variable importance was defined in two ways: by lasso penalized regression[54]; and by an ensemble method *featurerank*[55] that averaged over four different variable importance metrics as the mean of the reciprocal ranking[56]: *(i)* p-value; *(ii)* the *gain* metric in *ranger*[57] with 100 trees and default values for other hyperparameters; *(iii)* ranking the proportion of branches that used the predictor in *dbarts*[58] with 50 trees and default values for other hyperparameters; and *(iv)* SHAP values in *xgboost*[27] with 5,000 trees, 200 early stopping rounds, 5 folds, max depth = 4, shrinkage = 0.1, minobspernode = 10, subsample = 0.7, colsample_bytree = 0.8, and gamma = 5. For all other classifiers, variable importance was defined in three ways: *(i)* the *gain* measure in *ranger*[57] estimated using 1,000 trees with default values for other hyperparameters; *(ii)* ranking the proportion of branches that used the predictor in *dbarts*[58] using 20 trees with default values for other hyperparameters; and *(iii)* by using the same ensemble method as for the linear classifiers.

One other constraint was imposed in all feature selection methods other than the one based on the ensemble method. Specifically, we examined the exogenous bivariate correlations between all pairs of predictors and reduced the predictor set to remove variables with correlations of .80 or higher from the predictor set. This was done by selecting one predictor from each such set at random to retain in the predictor set without comparing magnitude of associations across predictors in the set with the outcome. This was done before using the feature selection method described above to reduce the predictor set further. This method was not used in the ensemble method, though, where we retained all predictors with significant univariable associations with the outcome before implementing the ensemble feature selection method.

Feature extraction for the NLP and LN models: In evaluating the incremental value of adding the NLP and LN SDoH variables to the Base model, we started with the 250 Base model predictors that were selected to be most important in terms of SHAP values in the training sample. This number was selected because predictors beyond the top 250 had SHAP values very close to 0. We then added all NLP term or topic variables or LN measures to the predictor set that had significant univariable associations with 12-month suicide in the training sample (Table 3). The same feature screening methods were then applied to these predictor sets as in the Base model.

Simultaneous hyperparameter tuning and variable selection: A total 1,845 estimators were defined by the cross-classification of the hyperparameter tuning profiles and feature selection methods. Individual-level predicted values were created for each of these estimators in the 10% metalearner estimation sample based on the models trained on the 50% training sample. Metalearner weights were then estimated in this 10% sample to select hyperparameter values, estimation algorithms, and predictors simultaneously. In the case of the lasso model, predictions based on the two variable selection methods were compared in the 10% metalearner estimation sample to arrive at the better lasso classifier.

Calibration: The metalearner weights for the SL models estimated in the 10% metalearner estimation sample were then applied to the 10% calibration sample to estimate logistic and isotonic regression models to calibrate the predicted probabilities produced by each of these models to the association between predicted and observed suicide distribution in the calibration sample. The same two calibration model transformations were used for the lasso model. The isotonic regression required using a nonparametric locally weighted scatterplot smoother, which we set to have a 0.75 bandwidth.[59]

Super Learner ensemble model training: As noted above, four SL ensembles were trained. The 1st used only the structured features from the base model. The 2nd and 3rd used the structured features in addition to either the NLP or LN features (referred to below as the NLP and LN models, respectively). The 4th used structured, NLP, and LN features. A 5th model was a simple benchmark lasso model.

Net benefit as an integration of information about discrimination and calibration: It was noted in the text that net benefit (NB) was defined as the observed number of true positives detected relative to the discounted number of false positives detected at each threshold for each model, where discounting was defined by the p/q break-even point implied by setting the decision threshold at p, where p=the predicted probability of suicide below which the intervention would not be provided and q=1-p.[60] This kind of discounted comparison usefully combines information about discrimination and calibration to address the fact that occasions often arise when one competing model will have better discrimination and another competing model will have better calibration. We divided NB by the observed suicide rate at each risk horizon to allow comparison of results across horizons, creating a standardized NB (SNB) that has an upper bound of 1.0. The net benefit of providing intensive case management to 100% of patients (the treat-all strategy) over a 12-month risk horizon at a given discount rate (DR) would be SR – (100,000-SR) x DR, where SR=the suicide rate in the population. At the decision threshold of 150 suicides per 100,000 hospitalization-years, for example, DR would be 150/(100,000-150) and NB of the treat-all strategy would be 112.6/100,000 patients. If SR was 262.5, as it was over the 12-month risk horizon in the prospective validation sample, this NB would be 42.9% as high as the unattainable optimal NB of 26.2 (ie, of knowing in advance exactly which 262.5 patients would die out of 100,000). 42.9% would be the SNB. SNB was compared across models at predicted 12-month suicide risk decision thresholds between 150 suicides/100,000 hospitalizations (roughly half the population mean) and 500 suicides/100,000 hospitalizations (roughly two times the population mean). 12-month decision thresholds were used across all risk horizons based on the assumption that intervention would be targeted for the outer limit risk horizon.

Predictor importance: As noted in the body of the text, predictor importance was examined using the model-agnostic kernel Shapley Additive Explanations (SHAP) method.[61] This method estimates the effect of changing a predictor from its observed score to the sample mean averaged across all logically possible permutations of other predictors. The mean of this "SHAP value" for a given predictor across all hospitalizations is 0. However, the mean *absolute* SHAP value provides useful information about the average importance of the predictor. A mean absolute SHAP value can also be created for classes of predictors combined or, for that matter, for all predictors in the model by adding up the signed SHAP values for each individual across the multiple predictors, calculating the absolute value of that sum, and then computing the mean of that sum. It is noteworthy that the means for individual predictors do not sum to the overall mean because most patients have a combination of some predictors with positive values and others with negative values. A beeswarm plot of observed individual-level predictor scores by SHAP values shows the dominant direction of association, but it is not possible to examine beeswarm plots for sets of predictors because there is no sensible way to make sense of an observed individual-level sum of predictor scores given that predictors differ in their metrics. Proportional mean absolute SHAP values ($SHAP_P$) can be calculated, though, by dividing mean absolute SHAP values of classes and important predictors within classes by the mean absolute SHAP value of the entire model.

Results

Classifier performance: As noted above, a diverse set of classifiers was included in the SL ensembles (eTable 5). However, only 5 classifiers had nonzero metalearner weights in the Combined model. These included one support vector machine with a metalearner weight of .618, two XGBoost, one with a weight of .348 and the other with a small weight, and two neural networks with small weights (eTable 9).

SHAP values: As noted in the main text, each observation (ie, hospitalization) gets its own SHAP value for each predictor based on estimating the effect on the predicted outcome for that observation of changing the observation's score on the predictor from the observed value to the mean across all logically possible combinations of other predictors. This means that the SHAP value can be positive for some observations and negative for others if interactions exist between the focal predictor and other predictors. That is why the mean is computed across observations of absolute rather than signed SHAP values to convey a sense of relative importance of predictors. However, the mean absolute SHAP value conveys no information about the direction of the association. This is done by computing a beeswarm plot in which the signed SHAP value for each observation is plotted against the mean absolute SHAP value. Inspection of the density of this plot conveys information about the dominant direction of association. A simple + or – summary of the dominant sign of these variable-specific associations based on the beeswarm plot (eFigure 1) was presented in Figure 2. More detailed analysis of interactions is possible by cross-classifying SHAP values at the level of the individual observation (eg,[62,63]). However, given the purposes of our analysis we did not carry out such an investigation.

eTable 1. Baseline Administrative Predictors

Construct	**Variables[a]**
I. Psychopathological risk factors	
A. Diagnoses[15,16,18,20,34,64-67]	The Clinical Classifications Software Refined (CCSR)[68] is a hierarchical categorization system that groups ICD-9-CM[69] and ICD-10-CM[70] diagnosis and procedure codes into more manageable categories. We created variables for a diagnosis of each of the Mental, Behavioral and Neurodevelopmental disorders CCSR categories and counts of number of visits with each diagnosis in the past 30, 60, 90, and 180 days, and in the past year, past 2, and past 5 years before hospital admission. We created similar variables using the ICD Mental, Behavioral and Neurodevelopmental disorders diagnostic categories,[69,70] along with a summary measure for any Mental, Behavioral and Neurodevelopmental disorder ICD diagnosis and number of visits with any diagnosis. Additional variables were included to identify a diagnosis of homicidal ideation, number of visits for homicidal ideation, diagnosis of and number of visits with a diagnosis of the Polytrauma Clinical Triad,[71] which is the co-occurrence of PTSD, TBI, chronic pain, and depression, each in the 7 time periods prior to hospitalization.
B. Treatments	
Psychiatric hospitalizations[64,65,67,72-74]	Previous psychiatric hospitalizations and noncompliance with treatment are both known risk factors for suicide, which we operationalized by creating dichotomous variables for each, a continuous count of number of days hospitalized in the 7 time periods before current admission, and number of times noncompliance with treatment was indicated in the patients record at each time period before hospitalization. We also obtained information on involuntary psychiatric hospitalizations and created indicators for any court-ordered psychiatric hold in the past 5 years and entire VHA history, emergency hospitalization/order of detention in the past 5 years and entire VHA history, variables for possible, probable, and definite involuntary holds in the past 5 years, and any type of involuntary psychiatric hospitalization/commitment in the past 2 years, past 5 years before current admission, and the entire VHA history.
Substance-related encounters[16,75]	HCPCS and CPT codes[76-78] were used to identify patients that received any of the following substance-related treatment/services (and number of visits receiving treatment/services) at the 7 time periods before hospital admission: alcohol or drug-related treatment/services (eg, behavioral counseling, substance misuse assessment), severe alcohol or drug-related treatment/services (eg, medication assisted treatment, residential addiction program), and nicotine-related treatment/services (eg, counseling, pharmacotherapy). Dichotomous and continuous count variables were created for each treatment/service received.
Other mental/behavioral health-related encounters[16,17,65,66,79,80]	Variables (dichotomous and continuous count for number of visits) for any CPT[76] codes for screening/examination/diagnosis of severe depression and HCPCS[77] codes for refractive depression (ie, patient did not remit after 6-12 months as measured by the PHQ-9) were included, along with variables to indicate receipt of family psychotherapy, any type of psychotherapy, ECT, and sleep apnea treatment/services in the 7 time periods before hospital admission.[78] We also identified patients who received any intense/crisis outpatient psychiatric treatment/services (including partial hospitalization or day treatment/services) and behavioral health residential treatment and the number of times receiving either type of treatment/service in the 7 time periods before hospital admission.[78]

eTable 1. Baseline administrative predictors (Continued)	
Construct	**Variables[a]**
I. Psychopathological risk factors	
B. Treatments	
Psychotropic medications[18,20,34,65,66,81-85]	The VA National Formulary (VANF) is a listing of drugs and supplies available at all VA facilities. The central nervous system (CNS) medications are divided into 12 minor classes and 21 subclasses, along with several subclasses of investigational CNS medications.[86] We classified the CNS medications into 19 categories: opioid analgesics, non-opioid analgesics, antimigraine medications, anesthetics, sedatives/hypnotics, anticonvulsants, antiparkinsonian medications, antivertigo medications, tricyclic antidepressants, MAOIs, other antidepressants (including investigational antidepressants), any antidepressant, antipsychotics, investigational antipsychotics/drugs for PTSD, lithium, stimulants, other CNS medications (including other investigational drugs for psychiatric diseases), other antidotes/deterrents, other CNS investigational medications (investigational analgesics, anesthetics, anti-anxiety drugs, anticonvulsants, drugs for mania and bipolar disorders, and drugs for Parkinson's disease) and created continuous count variables for the number of medications prescribed in each category in the 7 time periods prior to hospitalization.
Protective medications[87]	Antipsychotic medications have a wide range of side effects, including problems such as parkinsonism (tremor, rigidity), weight gain, akathisia, and tardive dyskinesia. Some of these side effects carry risks, including suicide (eg, akathisia).[88] We identified 17 medications known to offset the deleterious side effects of antipsychotics (amantadine, atenolol, benztropine, biperiden, clonazepam, deutetrabenazine, diazepam, diphenhydramine, lorazepam, metformin, metoprolol, orphenadrine, procyclidine, propranolol, tetravenazine, trihexyphenidyl, valbenazine) and created a 0-17 continuous count variable at each time period for the number of medications prescribed to offset side effects of antipsychotics.[b]
C. Suicidality[16,18,67,89,90]	Suicide and self-inflicted injury were characterized in the 7 time periods prior to hospital admission. Dichotomous variables were created using ICD-9-CM,[69] ICD-10-CM,[70] and CCSR[68] diagnosis codes for suicidal ideation, intentional self-harm, and suicide attempt, along with counts of number of visits with each diagnosis and number of suicide attempts in the 7 time periods before admission. VHA Patient Record Flags[91] were used to identify if the patient was at high risk for suicide at the time of admission and in the 7 time periods before admission.

eTable 1. Baseline administrative predictors (Continued)	
Construct	**Variables**[a]
II. Physical disorders	
A. Diagnoses[19,20,65,67,92-97]	Physical disorders were classified into 508 categories using the CCSR categorization system[68] and variables to indicate the presence of each diagnosis code and count of visits with each diagnosis code in the 7 time periods prior to hospitalization were created. We also distinguished several physical health problems based on previous research to be associated with suicide (eg,[19,65]) using ICD codes[69,70] and created dichotomous and count variables for number of visits in the 7 time periods prior to hospitalization for each of the following: 1) any headache syndromes, other headache syndromes, tension-type headaches, and tension-type headaches unspecified; 2) diagnosis of each of the Chronic Overlapping Pain Conditions,[98] which include fibromyalgia, IBS, interstitial cystitis/bladder pain syndrome, vulvodynia, migraines, chronic tension-type headaches, temporomandibular disorder, chronic fatigue syndrome, endometriosis with pain, and chronic low back pain; 3) diagnosis of each of the 13 pain-related diagnostic clusters from the Pain Condition Crosswalk[99]: back pain, neck pain, limb/extremity/joint pain and any non-systemic noninflammatory arthritic disorders, fibromyalgia, headaches, orofacial/ear and temporomandibular disorder pain, abdominal/bowel pain, urogenital/pelvic and menstrual pain, musculoskeletal chest pain, neuropathy, systemic disorders/diseases causing pain, fractures/contusions/sprains/strains, and other painful conditions; 4) moderate/severe pain at 2+ visits, defined as a score of 4+ on the 0-10 PI-NRS[100]; 5) chronic pain at 2+ visits, defined as a score of 7+ on the 0-10 PI-NRS[100]; 6) worst pain on the 0-10 PI-NRS; 6) any contact/exposure to infectious or communicable disease or encounter/need for vaccination.
B. Treatments	
Medical procedures/encounters[15, 101]	Variables to identify patients that received any pain-related treatment/services or procedures (eg, HCPCS code for leg pain measured by the VAS, CPT code for physical therapy, CPT code for nerve block) and fMRI scans in the 7 time periods before hospital admission were created (along with number of visits for each treatment/service) using HCPCS/CPT codes.[76,77,102] ICD-9-CM[69] and ICD-10-CM[70] codes were used to create a variable for any visit/encounter for physical, occupational, vocational, or rehabilitation therapy and number of visits/encounters in the 7 time periods before hospitalization.
Non-psychotropic medications[20,103-106]	Non-psychotropic medications were collapsed into 29 categories using the VANF[86] and continuous count variables were created to represent number of drugs prescribed in each class in the 7 time periods prior to hospitalization. We also created an indicator for a prescription of vitamin D at each time period, as this is hypothesized to decrease depression and other mental/physical disorders that are frequently comorbid with suicide and self-harm.[107]

eTable 1. Baseline administrative predictors (Continued)	
Construct	**Variables[a]**
II. Physical disorders	
C. Medications classified by FDA as increasing risk of suicide[21,108,109]	The FDA requires that drug manufacturers list adverse side effects on the drug product labels and package inserts. There are 3 sections that address adverse side effects: boxed warnings, warnings and precautions, and adverse reactions, in order of severity level. We searched the FDA Label Database[110] for FDA-approved drug labeling documents that listed suicide as an adverse drug reaction. Specific search terms were "suicidality, suicidal behavior, suicidal ideation, suicide attempt, suicidal, and suicide." We found 55 drugs that indicated suicide as an adverse side effect in the box warning section of the drug label, 137 drugs in the warnings and precautions section, and 79 with suicide in the adverse reactions section. We created variables for the number of drugs prescribed with each type of warning and a count of the number of drugs prescribed with any FDA warning in the 7 time periods before hospitalization. See eTable 4 for a complete list of medications.
III. Facility-level quality indicators[82,111]	Variables to characterize the facility where the patient was hospitalized included number of medical/social positions lost, ratio of medical/social positions lost/onboards, and mean length of psychiatric hospitalizations (in days) in the year prior to hospitalization. We also included variables for drive time in minutes to the closest VHA primary care, secondary care, and tertiary care facility.
IV. Social determinants of health	
A. Patient-level	
Accidents[67]	14 major categories of accidents were identified using ICD-9-CM[69] and ICD-10-CM[70] codes: railway accidents, motor vehicle traffic accidents, motor vehicle nontraffic accidents, other road vehicle accidents, water transport accidents, air and space transport accidents, vehicle accidents not elsewhere classifiable, accidental poisoning by drugs/medicinal substances/biologicals, accidental poisoning by other solid and liquid substances/gases/vapors, accidental falls, accidents caused by fire and flames, accidents due to natural and environmental factors, accidents caused by submersion/suffocation/foreign bodies, and other accidents. We created dichotomous variables for each along with counts of the number of codes present for each of the 14 different categories of accidents in the 7 time periods prior to hospitalization.
Abuse/assault[112]	Dichotomous variables were created to distinguish patients who were victims of rape, victims of physical assault, and perpetrators of child or adult abuse in the 7 time periods prior to hospitalization. Continuous count variables were also included to indicate the number of visits in the 7 time periods where any ICD-9-CM[69] or ICD-10-CM[70] code was present for the 3 experiences.
Homelessness[16,112]	Homelessness in the 7 time periods prior to hospitalization was identified using ICD codes, VHA Patient Treatment File codes, and VHA outpatient clinic stop codes.[113]

eTable 1. Baseline administrative predictors (Continued)	
Construct	**Variables[a]**
IV. Social determinants of health	
A. Patient-level	**A. Patient-level**
Psychosocial problems[15,24,112,114]	We defined 5 other categories of psychosocial problems using ICD-9-CM[69] and ICD-10-CM[70] codes and created dichotomous and count variables in the 7 time periods for each: 1) problems with housing, material resources, and social isolation; 2) separation, divorce, or bereavement; 3) counseling for marital problems; 4) unemployment; and 5) any other psychosocial circumstance or stressor.
B. Socio-demographics[16,65,90,115,116]	Socio-demographic variables included age, gender (male, female), race-ethnicity (Non-Hispanic Black, Non-Hispanic White, Hispanic, other), marital status (currently married, never married, divorced/previously married, separated, widowed), religion (Baptist, Evangelical, Methodist, Protestant, Roman Catholic, other Christian, other non-Christian, none), income, period of service (Pre-Vietnam, Vietnam era, Post-Vietnam, Persian Gulf War), census region (Northeast, South, Midwest, West), and urbanicity (metro area with population of 1 million+, metro area with population of 250,000 to 1 million, metro area with population less than 250,000, urban area with population of 20,000+, urban/completely rural area with population less than 20,000).

Abbreviations: ICD-9-CM, International Classification of Diseases, Ninth Revision Clinical Modification; ICD-10-CM, International Classification of Diseases, Tenth Revision Clinical Modification; PTSD, posttraumatic stress disorder; TBI, traumatic brain injury; VHA, Veterans Health Administration; HCPCS, Healthcare Common Procedure Coding System; CPT, Current Procedural Terminology; PHQ-9, Patient Health Questionnaire-9; ECT, electroconvulsive therapy; VA, Veterans Administration; MAOIs, monoamine oxidase inhibitors; IBS, irritable bowel syndrome; PI-NRS, Pain Intensity-Numeric Rating Scale; VAS, visual analog scale; fMRI, functional magnetic resonance imaging; FDA, Food and Drug Administration.

[a]We included dichotomous, ordinal, interval, and ratio variables which were standardized to a mean of 0 and variance of 1, with values more than 3 standard deviations above or below the mean truncated to 3 or -3. Variables that were rare (ie, associated with fewer than 5 12-month suicides in the training sample) or not significant (ie, did not have 10-fold cross-validated (10F-CV) univariable area under the receiver operating characteristic curve (AUC-ROC) significantly >.50 at.05 level of significance using one-sided tests) were excluded to reduce the risk of over-fitting.

[b]The variable was created by multiplying the number of medications prescribed x a dichotomous 0-1 variable for also taking an antipsychotic medication.

eTable 2. Social Determinants of Health: Geospatial Indicators

Construct	**Variables**[a]
A. Demographics	
Household characteristics[117-121]	Mean household size, Count of households, Percent of households with 1 resident, Percent of families with female heads of household
B. Economic conditions	
GDP[122,123]	Per capita GDP in thousands of chain-linked 2012 dollars,[b] GDP in thousands of current dollars, Yearly percent change (chain-type quantity index for real GDP)
Income[118,124]	Per capita personal income by residence in thousands of dollars
Employment[117,118,125]	Monthly unemployment rate
Employment sector[14,117,126,127]	Percent and total number of establishments and Percent and total number employed in the Agriculture, forestry, fishing, hunting, and mining sector, Arts, entertainment, recreation, and restaurants sector, Construction sector, Education, healthcare, and social assistance sector, Finance, insurance, and real estate sector, Information sector, Manufacturing sector, Mental health services sector, Alcohol outlets (on-premise) sector, Alcohol outlets (off-premise) sector, Professional, science, and management sector, Retail and trade sector, Transportation and warehouse sector, Wholesale trade sector, and Other sectors
C. Health & access to health care	
Healthcare coverage[118,128]	Medicaid eligible rate
Nursing homes[119,129]	Per capita number of nursing homes per month, Proportion of for-profit facilities, Proportion of non-profit facilities, Proportion of county-supported facilities, Proportion of county-owned facilities, Proportion of government facilities, Per capita number of Medicare/Medicaid certified beds, Average number of residents in Medicare/Medicaid certified beds, Proportion of available beds that are occupied by residents
Birth rates[82,122,130]	Teen birth rate (ages 15-19) per 1,000 females, Percent of very low weight births (<2,500 grams) among live births
Mortality rates[35,82,131-133]	Years of potential life lost before age 75 (age-adjusted) per 100,000 people, Infant mortality rate (<1 year old) from all causes per 100,000 infants, Mortality rates per 100,000 people due to Alcohol, Drugs, Liver disease, HIV/AIDS, Homicide, Suicide by any method, Suicide by firearm, Motor vehicle accidents, Other external causes
Health behaviors[122,134-138]	Percent of obese adults[c] (BMI ≥ 30 kg/m^2), Percent of physically inactive adults,[c] Percent of adult[c] smokers, Percent of binge/heavy drinkers,[c] Newly diagnosed chlamydia cases per 100,000 people, HIV rate per 100,000 people, Total HIV cases, Opioid prescribing rate per 100 people
Quality of health[82,135,139,140]	Percent of adults reporting fair or poor health (age-adjusted), Average number of days in a month with poor physical health (age-adjusted), Average number of days in a month with poor mental health (age-adjusted), Composite health outcomes measure,[d] Overall health outcome summary score[d]

eTable 2. Social determinants of health: Geospatial indicators (Continued)	
Construct	**Variables**[a]
D. Homelessness	
Annual homelessness rate[14,82,141]	Rate of homelessness, Rate of unsheltered homelessness per 1,000 Census Tract population on a single given night in January
E. Transience	
Students[142,143]	Percent of 4+ year colleges/universities, Percent of less than 4-year colleges/universities, Percent of private institutions, Percent of public institutions
Urbanicity[117,120,144]	Rural-Urban Continuum Codes,[e] Proportion of metropolitan areas, Proportion of urban areas, Proportion of rural areas
F. Crime & incarceration rate	
Incarceration rate[14,145-147]	Annual number of inmates per 10,000 people, Proportion of convicted inmates, Proportion of American Indian/Alaskan Native inmates, Proportion of Asian inmates, Proportion of Black/African American inmates, Proportion of Hispanic/Latinx inmates, Proportion of Native Hawaiian/other Pacific Islander inmates, Proportion of White inmates, Proportion of inmates of all other races, Proportion of adult female inmates, Proportion of adult male inmates, Proportion of juvenile inmates
G. Environmental characteristics	
Disaster relief[14,148,149]	Rolling counts per month of FEMA disasters declared, FEMA Hazard Mitigation Grant Programs declared, FEMA Individual Assistance Programs declared, FEMA Individuals and Households Programs declared, and FEMA Public Assistance Programs declared during a 6-month, 12-month, and 3-year period for disaster response/recovery efforts
Coal mines & plants[14,150-152]	Percent of coal mines, Percent of coal-fired electric power plants

Abbreviation: GDP, gross domestic product; HIV/AIDS, human immunodeficiency virus, acquired immunodeficiency syndrome; kg, kilogram; m^2, meters squared; HIV, human immunodeficiency virus; FEMA, Federal Emergency Management Agency.

[a]All variables were standardized to a mean of 0 and variance of 1 and were measured at the county-level unless indicated otherwise. Variables that were rare (ie, associated with fewer than 5 12-month suicides in the training sample) or not significant (ie, did not have 10-fold cross-validated (10F-CV) univariable area under the receiver operating characteristic curve (AUC-ROC) significantly >.50 at.05 level of significance using one-sided tests) were excluded to reduce the risk of over-fitting.

[b]Inflation-adjusted measure of area's gross product, based on national prices for the goods and services produced within the area. The real estimates of GDP are measured in chained (2012) dollars.

[c]People aged 20+ years old.

[d]The county-level composite health outcomes measure is a sum of the following standardized variables: Years of potential life lost before age 75 (age-adjusted) per 100,000 people, Percent of adults reporting fair or poor health (age-adjusted), Average number of days in a month with poor physical health (age-adjusted), Average number of days in a month with poor mental health (age-adjusted), and Percent of very low weight live births (<2,500 grams). The overall health outcomes summary score is a sum of the variables (non-standardized forms) used in the composite health outcomes measure, with higher scores indicating worse county-level health outcomes.

[e]The Rural-Urban Continuum Codes (RUCC) is a 9-category coding system that groups metropolitan counties by population density and nonmetropolitan counties by urbanization and proximity to a metro area. Metropolitan areas are subdivided into 3 categories: counties in metropolitan areas with a population of 1 million+ (RUCC 1), population of 250,000-1 million (RUCC 2), and population of less than 250,000 (RUCC 3). Nonmetropolitan counties are subdivided into 6 categories: urban areas with a population of 20,000+ adjacent to a metropolitan area (RUCC 4), urban areas with a population of 20,000+ not adjacent to a metropolitan area (RUCC 5), urban areas with a population of 2,500-19,999 adjacent to a metropolitan area (RUCC 6), urban areas with a population of 2,500-19,999 not adjacent to a metropolitan area (RUCC 7), completely rural areas or urban areas with a population of less than 2,500 adjacent to a metropolitan area (RUCC 8), and completely rural areas or urban areas with a population of less than 2,500 not adjacent to a metropolitan area (RUCC 9).

eTable 3. Social Determinants of Health: LexisNexis Predictors[7,153]

Construct	**Variables**[a]
I. Household & neighborhood characteristics	
Household composition	Number of household members on record, Number of relative and associate households on record,[b] Distance to closest first degree relative or close associate.[b,c]
Voting records	Voter registration status
Licenses	Number of household members with hunting and fishing licenses, concealed carry, and explosive device permits
Neighborhood crime	Neighborhood Crime Index[d]
II. Assets & income	
Assets	Individual owns current residence, Individual owns assets,[e] Number of vehicles currently registered to individual, Total appraised dollar value of all real property currently owned, Wealth Index,[f] Economic Trajectory Index[g]
Personal income	Annual income 1 year ago,[h] Annual income 2 years ago,[h] Difference in 2-year annual income,[h] Level of banking experience[i]
III. Residential stability	
Address changes	Moved to a downscale property in the past 5 years,[j] Address Stability Index[k]
IV. Criminal, financial, & identity records	
Derogatory criminal & financial records	Number of lifetime arrests, Number of lifetime felony convictions, Number of lifetime bankruptcy filings, Number of lifetime evictions, Number of derogatory public records on file,[l] Number of court records on file,[m] Any arrests, felony convictions, bankruptcy filings, evictions, or real property sold in the past 12 months, Number of derogatory public records reported in the past 12 months,[l] Investigated for an accident in the past 12 months, Court Record Severity Index[n]
Identity activity	Recent Risk Activity Index,[o] Max Identity Fraud-Risk Level[p]

[a]We included dichotomous, ordinal, interval, and ratio variables which were standardized to a mean of 0 and variance of 1, with values more than 3 standard deviations above or below the mean truncated to 3 or -3. Variables that were rare (ie, associated with fewer than 5 12-month suicides in the training sample) or not significant (ie, did not have 10-fold cross-validated (10F-CV) univariable area under the receiver operating characteristic curve (AUC-ROC) significantly >.50 at.05 level of significance using one-sided tests) were excluded to reduce the risk of over-fitting.
[b]People who have shared address history, assets, or debts.
[c]Less than 25 miles, 25-100 miles, or over 100 miles between individual and closest first degree relative/close associate.
[d]A 0-200 rating scale of neighborhood crime based on FBI data.
[e]Assets include real property, aircraft, or watercraft.
[f]Based on the value of property and other assets, where 1=very low and 5=high or very high wealth.
[g]Index describing the type (either single family or condo/town home) and value of property at the current address compared to the address immediately prior to current address. A value of 1 or 2 indicates that the current address property type and value is less or much less than the most recent address (ie, move from upscale to downscale address), 3 denotes current and most recent are equal (ie, lateral move), and 4 or more indicates that the current address is greater than most recent address (ie, move from downscale to upscale address).
[h]Rounded to nearest $1,000, with income less than $20,000 annually coded as 19,999, between $20,000 and $250,000 coded to actual dollar amount, and greater than $250,000 annually coded 250,999.
[i]Coded 0-2 where 0 = likely unbanked, 1 = likely underbanked, and 2 = likely or highly banked.
[j]Moving from an apartment to single-family dwelling unit, moving from a single-family dwelling unit to another single-family dwelling and current value is more than $150,000 or current value is $0.00, or moving way down or staying down.
[k]Coded 1-5 where 1 = highly stable, fewer moves, or fewer address changes and 5 = highly unstable, more moves, or more address changes.
[l]Felonies, liens, bankruptcies, and evictions.
[m]Includes felonies, liens, bankruptcies, evictions, judgements, and misdemeanors.
[n]Court records were ranked in order of severity level, where a criminal felony on file was ranked the worst/most severe (coded 5), followed by an eviction (coded 4), a lien (coded 3), a criminal non-felony (coded 2), and a bankruptcy (coded 1). If no court records were on file the variable was coded to 0.

[o] Index measuring level of risky identity-related activity in the past 3 months, such as credit card purchases, name changes, etc. Higher values on the index indicate more evidence of high risk activity.
[p] Highest fraud-risk level score out of all fraud-risk level variables. Each variable has a range of 1-9 with higher scores indicating higher identity fraud risk.

eTable 4. Medications Classified by FDA as Increasing Risk of Suicide[110]

VANF drug class	**Medication**	**FDA warning type**
I. CNS Medications		
A. Analgesics		
Opioids	acetaminophen & oxycodone	Adverse reactions
	acetaminophen & propoxyphene[a]	Boxed warning
	acetaminophen & tramadol	Warnings & precautions
	hydromorphone	Adverse reactions
	levorphanol	Adverse reactions
	oxycodone[b]	Adverse reactions
	propoxyphene[a]	Boxed warning
	tapentadol	Adverse reactions
	tramadol	Warnings & precautions
	tramadol & .gamma.-aminobutyric acid[c]	Adverse reactions
	tramadol & gaba[c]	Warnings & precautions
Opioid antagonists	naltrexone	Warnings & precautions
Non-opioid analgesics	aspirin & meprobamate	Warnings & precautions
	ziconotide	Warnings & precautions
B. Anticonvulsants	brivaracetam	Warnings & precautions
	cannabidiol	Warnings & precautions
	carbamazepine	Warnings & precautions
	cenobamate	Warnings & precautions
	clobazam	Warnings & precautions
	cyclo/gaba 10/300 pack	Warnings & precautions
	divalproex	Warnings & precautions
	eslicarbazepine	Warnings & precautions
	ethosuximide	Warnings & precautions
	ethotoin[d]	Warnings & precautions
	felbamate	Warnings & precautions
	fenfluramine	Warnings & precautions
	gabapentin	Warnings & precautions
	gabapentin & .gamma.-aminobutyric acid[c]	Warnings & precautions
	gabapentin & lidocaine[c]	Warnings & precautions
	lacosamide	Warnings & precautions
	lamotrigine	Warnings & precautions
	levetiracetam	Warnings & precautions
	methsuximide	Warnings & precautions
	oxcarbazepine	Warnings & precautions
	perampanel	Warnings & precautions
	phenytoin	Warnings & precautions
	pregabalin	Warnings & precautions
	primidone	Warnings & precautions
	rufinamide	Warnings & precautions
	stiripentol	Warnings & precautions
	tiagabine	Warnings & precautions
	topiramate	Warnings & precautions
	trimethadione[e]	Warnings & precautions
	valproic acid	Warnings & precautions
	vigabatrin	Warnings & precautions
	zonisamide	Warnings & precautions

eTable 4. Medications classified by FDA as increasing risk of suicide[110] (Continued)		
VANF drug class	**Medication**	**FDA warning type**
I. CNS Medications		
C. Antidepressants		
MAOIs	isocarboxazid	Boxed warning
	phenelzine	Boxed warning
	selegiline patch	Boxed warning
	tranylcypromine	Boxed warning
NDRIs	bupropion	Boxed warning
	bupropion & tyrosine[c]	Boxed warning
SARIs	trazodone	Boxed warning
	trazodone & choline[c]	Boxed warning
SNRIs	desvenlafaxine	Boxed warning
	duloxetine	Boxed warning
	levomilnacipran	Boxed warning
	milnacipran	Boxed warning
	venlafaxine	Boxed warning
	viloxazine	Boxed warning
SSRIs	citalopram	Boxed warning
	citalopram & choline[c]	Boxed warning
	escitalopram	Boxed warning
	fluoxetine	Boxed warning
	fluoxetine & choline[c]	Boxed warning
	fluvoxamine	Boxed warning
	paroxetine	Boxed warning
	sertraline	Boxed warning
	vilazodone	Boxed warning
	vortioxetine	Boxed warning
TeCAs	maprotiline[f]	Boxed warning
	mirtazapine	Boxed warning
Tricyclics	amitriptyline	Boxed warning
	amitriptyline & choline[c]	Boxed warning
	amoxapine	Boxed warning
	clomipramine	Boxed warning
	desipramine	Boxed warning
	doxepin	Boxed warning
	imipramine	Boxed warning
	nortriptyline	Boxed warning
	protriptyline	Boxed warning
	trimipramine	Boxed warning
Other	brexanolone	Warnings & precautions
	esketamine nasal spray	Boxed warning
	nefazodone	Boxed warning
D. Antidotes/deterrents	acamprosate	Warnings & precautions
	varenicline	Warnings & precautions
E. Antimigraine agents	sumatriptan[g]	Adverse reactions
	sumatriptan, camphor, & menthol[c]	Adverse reactions
	sumatriptan, mentholum, belladonna, iris, & sanguinaria	Adverse reactions
	sumatriptan & ondansetron[c]	Adverse reactions

eTable 4. Medications classified by FDA as increasing risk of suicide[110] (Continued)		
VANF drug class	**Medication**	**FDA warning type**
I. CNS Medications		
F. Antiparkinson agents	Carbidopa	Warnings & precautions
	carbidopa, entacapone, & levodopa	Warnings & precautions
	carbidopa & levodopa	Warnings & precautions
	pergolide[h]	Warnings & precautions
	pramipexole[i]	Adverse reactions
	ropinirole[j]	Adverse reactions
G. Antipsychotics	aripiprazole	Boxed warning
	asenapine	Adverse reactions
	brexpiprazole	Boxed warning
	cariprazine	Boxed warning
	iloperidone	Warnings & precautions
	lurasidone	Boxed warning
	olanzapine	Warnings & precautions
	perphenazine	Warnings & precautions
	quetiapine	Boxed warning
	ziprasidone	Warnings & precautions
H. Sedatives/hypnotics		
Barbiturates	amobarbital	Warnings & precautions
	pentobarbital[c]	Warnings & precautions
	phenobarbital	Warnings & precautions
	secobarbital[k]	Warnings & precautions
Benzodiazepines	alprazolam	Warnings & precautions
	alprazolam & choline[c]	Warnings & precautions
	chlordiazepoxide	Warnings & precautions
	clonazepam	Warnings & precautions
	clorazepate	Warnings & precautions
	diazepam	Warnings & precautions
	diazepam & choline[c]	Warnings & precautions
	estazolam	Warnings & precautions
	flurazepam	Warnings & precautions
	lorazepam	Warnings & precautions
	midazolam nasal spray	Warnings & precautions
	quazepam	Warnings & precautions
	temazepam	Warnings & precautions
	temazepam & choline[c]	Warnings & precautions
	triazolam	Warnings & precautions
Other	buspirone	Adverse reactions
	eszopiclone	Warnings & precautions
	lemborexant	Warnings & precautions
	meprobamate	Warnings & precautions
	ramelteon	Warnings & precautions
	suvorexant	Warnings & precautions
	zaleplon	Warnings & precautions
	zolpidem	Warnings & precautions
	zolpidem & choline[c]	Warnings & precautions
I. Stimulants		
Amphetamines	amphetamine	Warnings & precautions
	amphetamine & dextroamphetamine	Warnings & precautions
	dextroamphetamine	Warnings & precautions
	lisdexamfetamine	Warnings & precautions
	methamphetamine	Warnings & precautions

eTable 4. Medications classified by FDA as increasing risk of suicide[110] (Continued)		
VANF drug class	**Medication**	**FDA warning type**
I. CNS Medications		
I. Stimulants		
Amphetamine-like	dexmethylphenidate	Warnings & precautions
	methylphenidate	Warnings & precautions
Other	armodafinil	Warnings & precautions
	modafinil	Warnings & precautions
	pitolisant	Adverse reactions
J. Other CNS medications		
CNS depressants	calcium, magnesium, potassium, & sodium oxybates	Warnings & precautions
	sodium oxybate	Warnings & precautions
Dementia/Alzheimer's	donepezil & memantine	Adverse reactions
	galantamine[l]	Adverse reactions
	memantine	Adverse reactions
	rivastigmine[m]	Adverse reactions
Other	amitriptyline & chlordiazepoxide	Boxed warning
	amitriptyline & perphenazine	Boxed warning
	atomoxetine	Boxed warning
	bupropion & naltrexone	Boxed warning
	fluoxetine & olanzapine	Boxed warning
II. Antihistamines	cetirizine	Adverse reactions
	levocetirizine	Adverse reactions
III. Antimicrobials		
Antibiotics	ciprofloxacin	Warnings & precautions
	cycloserine	Adverse reactions
	delafloxacin	Warnings & precautions
	gemifloxacin	Warnings & precautions
	levofloxacin	Warnings & precautions
	moxifloxacin	Warnings & precautions
	ofloxacin tablet	Adverse reactions
	rifapentine	Adverse reactions
Antifungals	ketoconazole[n]	Adverse reactions
	voriconazole	Adverse reactions
Antiretrovirals	Abacavir, dolutegravir, & lamivudine	Adverse reactions
	bictegravir, emtricitabine, & tenofovir	Adverse reactions
	cabotegravir	Adverse reactions
	cabotegravir & rilpivirine	Warnings & precautions
	cobicistat, elvitegravir, emtricitabine, & tenofovir	Adverse reactions
	dolutegravir	Adverse reactions
	dolutegravir & lamivudine	Adverse reactions
	dolutegravir & rilpivirine	Warnings & precautions
	doravirine	Adverse reactions
	doravirine, lamivudine, & tenofovir	Adverse reactions
	efavirenz	Warnings & precautions
	efavirenz, emtricitabine, & tenofovir	Warnings & precautions
	efavirenz, lamivudine, & tenofovir	Warnings & precautions
	emtricitabine, rilpivirine, & tenofovir	Warnings & precautions
	enfuvirtide	Adverse reactions
	raltegravir	Adverse reactions
	rilpivirine	Warnings & precautions

eTable 4. Medications classified by FDA as increasing risk of suicide[110] (Continued)		
VANF drug class	**Medication**	**FDA warning type**
III. Antimicrobials		
Antivirals	amantadine	Warnings & precautions
	ledipasvir & sofosbuvir	Adverse reactions
	nelfinavir	Adverse reactions
	ombitasvir, paritaprevir, & ritonavir[o]	Adverse reactions
	ribavirin	Warnings & precautions
	saquinavir	Adverse reactions
	sofosbuvir	Adverse reactions
IV. Antineoplastics		
Anticancer	alemtuzumab	Adverse reactions
	avapritinib	Adverse reactions
	blinatumomab	Adverse reactions
	bortezomib	Adverse reactions
	entrectinib	Warnings & precautions
	lorlatinib	Warnings & precautions
	oxaliplatin[p]	Adverse reactions
	sacituzumab	Adverse reactions
	thiotepa	Adverse reactions
	triptorelin	Adverse reactions
Hormones	histrelin	Adverse reactions
	leuprolide	Adverse reactions
	leuprolide & norethindrone	Adverse reactions
	relugolix, estradiol, & norethindrone	Warnings & precautions
V. Antiparasitics		
Antimalarials	chloroquine	Adverse reactions
	hydroxychloroquine	Warnings & precautions
	mefloquine	Warnings & precautions
	quinine	Adverse reactions
	tafenoquine	Warnings & precautions
VI. Autonomics	metoclopramide	Warnings & precautions
VII. Cardiovascular medications		
Antihypertensives	hydralazine, hydrochlorothiazide, & reserpine 1/98[q]	Warnings & precautions
	polythiazide & reserpine[q]	Warnings & precautions
Ca channel blockers	amlodipine & celecoxib	Adverse reactions
VIII. Dermatological agents		
Antiacne agents	dapsone gel	Adverse reactions
	isotretinoin	Warnings & precautions
Antipsoriatics	acitretin	Adverse reactions
	brodalumab	Boxed warning & REMS[r]
IX. GI medications		
Antiobesity	lorcaserin	Warnings & precautions
	phentermine & topiramate	Warnings & precautions
	setmelanotide	Warnings & precautions
Other	certolizumab	Adverse reactions
	chlordiazepoxide & clidinium	Warnings & precautions
	magnesium, bisacodyl, petrolatum, polyethylene glycol 3350, & metoclopramide[c]	Warnings & precautions
	octreotide[s]	Adverse reactions
	prucalopride	Warnings & precautions
	tegaserod	Warnings & precautions

eTable 4. Medications classified by FDA as increasing risk of suicide[110] (Continued)		
VANF drug class	**Medication**	**FDA warning type**
X. Herbs & alternatives	angelica sinensis radix, aralia quinquefolia, arg. nit., arsenicum alb., berber. aqui., capsicum, cinchona, digitalis, gelsemium, hypericum, ignatia, iodium, kali brom., kali carb., mag. phos., nat[c]	Warnings & precautions
XI. Hormones, synthetics, & modifiers		
Androgens	testosterone enanthate	Warnings & precautions
	testosterone gel[t]	Adverse reactions
	testosterone undecanoate capsule	Warnings & precautions
Contraceptives	drospirenone & estetrol	Adverse reactions
	ethinyl estradiol & levonorgestrel	Warnings & precautions
	ethinyl estradiol, norethindrone & ferrous	Adverse reactions
Glucocorticoids	deflazacort	Warnings & precautions
	dexamethasone[u]	Warnings & precautions
Hypoglycemic agents	liraglutide	Warnings & precautions
	semaglutide	Warnings & precautions
Progestins	progesterone	Adverse reactions
Other	elagolix	Warnings & precautions
	elagolix, estradiol & norethisterone	Warnings & precautions
	ethinyl estradiol & norethindrone[v]	Adverse reactions
	nafarelin nasal spray	Adverse reactions
	prasterone & ibuprofen[c]	Adverse reactions
XII. Immunological agents		
Immunomodulators	imiquimod	Adverse reactions
Immunostimulants	aldesleukin	Adverse reactions
	interferon alfa-2b	Warnings & precautions
	interferon beta-1a	Warnings & precautions
	interferon beta-1b	Warnings & precautions
	peginterferon alfa-2a	Warnings & precautions
	peginterferon alfa-2b	Boxed warning
	peginterferon beta-1a	Warnings & precautions
Immunosuppressants	belimumab	Warnings & precautions
	daclizumab[w]	Warnings & precautions
	natalizumab	Adverse reactions
	thalidomide	Adverse reactions
Vaccines	human papillomavirus 9-valent vaccine recombinant	Adverse reactions
	human papillomavirus quadrivalent (types 6, 11, 16, and 18) vaccine recombinant	Adverse reactions
	meningococcal (groups a, c, y and w-135) oligosaccharide diphtheria crm197 conjugate vaccine	Adverse reactions
XIII. Musculoskeletal medications		
Antirheumatics	apremilast	Warnings & precautions
	celecoxib	Adverse reactions
	celecoxib, methyl salicylate, menthol, & capsaicin	Adverse reactions
Huntington's disease	deutetrabenazine	Boxed warning
	tetrabenazine	Boxed warning
Immunomodulators	glatiramer	Adverse reactions
Muscle relaxants	baclofen injection	Adverse reactions
	tizanidine	Adverse reactions

eTable 4. Medications classified by FDA as increasing risk of suicide[110] (Continued)		
VANF drug class	**Medication**	**FDA warning type**
XIV. Respiratory agents	beclomethasone	Adverse reactions
	montelukast	Boxed warning
	roflumilast	Warnings & precautions

Abbreviations: FDA, Food and Drug Administration; VANF, VA National Formulary; CNS, central nervous system; MAOIs, monoamine oxidase inhibitors; NDRIs, norepinephrine-dopamine reuptake inhibitors; SARIs, serotonin antagonist and reuptake inhibitors; SNRIs, serotonin-norepinephrine reuptake inhibitors; SSRIs, selective serotonin reuptake inhibitors; TeCAs, tetracyclic antidepressants; REMS, Risk Evaluation and Mitigation Strategies; Ca, calcium.
[a]Withdrawn from the market in 2010/2011 due to potential to cause fatal heart problems.
[b]Only in extended-release version of the FDA drug label.
[c]Unapproved drug but still available.[154]
[d]Discontinued in 2020 due to low demand.
[e]Discontinued in 1995 due to low demand but also thought to cause to birth defects. Still prescribed under compassionate use program to allow trimethadione - receiving patients access to the drug
[f]Discontinued in 2021 for unknown reasons.
[g]Suicide risk is listed as adverse side effect in 4/15/2021 drug label and prior versions, not in most recent versions.
[h]Withdrawn from the market in 2007 because of risk of serious damage to heart valves.
[i]Suicide risk is listed as adverse side effect in 10/13/2016 drug label and prior versions, not in most recent versions.
[j]Suicide risk is listed as adverse side effect in 9/11/2019 drug label and prior versions, not in most recent versions.
[k]Discontinued in 2022, unknown reasons but FDA declared it was not due to safety issues.
[l]Suicide risk is listed as adverse side effect in 6/13/2016 drug label and prior versions, not in most recent versions.
[m]Suicide risk is listed as adverse side effect in 9/9/2019 drug label and prior versions, not in most recent versions.
[n]Suicide risk is listed as adverse side effect in 9/12/2013 drug label and prior versions, not in most recent versions.
[o]Discontinued in 2018 because of changes in Hepatitis C treatment practices.
[p]Suicide risk is listed as adverse side effect in 9/22/2021 drug label and prior versions, not in most recent versions.
[q]Discontinued due to interactions and side effects of reserpine.
[r]Brodalumab is in the REMS program due to the high risk of suicidal ideation, behavior, and completed suicides in patients taking the drug. The brodalumab REMS program requires prescribers to be educated about the risk of suicide, to education patients about the risk, and closely monitor the use of the drug.
[s]Suicide risk is listed as adverse side effect in 3/30/2021 drug label and prior versions, not in most recent versions.
[t]Suicide risk is listed as adverse side effect in 3/30/2022 drug label and prior versions, not in most recent versions.
[u]Suicide risk is listed as adverse side effect in 7/28/2022 drug label and prior versions, not in most recent versions.
[v]Suicide risk is listed as adverse side effect in 6/1/2022 drug label and prior versions, not in most recent versions.
[w]Withdrawn from the market in 2018 due to link to serious inflammatory brain disorders.

eTable 5. Classifiers Used in the Super Learner Ensemble[a]

Algorithm	**Description**
I. Super Learner	
	Super Learner is an ensemble machine learning approach that uses cross-validation (CV) to select a weighted combination of predicted outcome scores across a collection of candidate algorithms (learners) to yield an optimal combination according to a pre-specified criterion that performs at least as well as the best component algorithm. R package: *Superlearner*.[40,44]
II. Learners in the Super Learner library	
A. Logistic regression	Maximum likelihood estimation with logistic link function. R package: stats.[155]
B. Elastic Net[b]	Elastic net is a regularization method that minimizes the problem of overlap among predictors by explicitly penalizing over-fitting with a composite penalty λ{MPP x Plasso + (1- MPP) X Pridge}mpp mppmppmp, where MPP is a mixing parameter penalty with values between 0 and 1 that controls relative weighting between the lasso penalty (Plasso) and the ridge penalty (Pridge). The parameter λ controls the total amount of penalization. The ridge penalty handles multicollinearity by shrinking all coefficients smoothly towards 0 but retains all variables in the model. The lasso penalty allows simultaneous coefficient shrinkage and variable selection, tending to select at most one predictor in each strongly correlated set, but at the expense of giving unstable estimates in the presence of high multicollinearity. The elastic net approach of combining the ridge and lasso penalties has the advantage of yielding more stable and accurate estimates than either ridge or lasso alone while maintaining model parsimony. R package: *glmnet*.[54] Hyperparameters: alpha = (0.0, 0.2, 0.4, 0.6, 0.8, 1.0).
C. Adaptive polynomial splines[a]	Adaptive spline regression flexibly captures both linear and piecewise non-linear associations as well as interactions among these associations by connecting linear segments (splines) of varying slopes and smooths to create piece-wise curves (basis functions). Final fit is built using a stepwise procedure that selects the optimal combination of basis functions. Adaptive polynomial splines are like adaptive splines but differ in the order in which basis functions (eg, linear versus nonlinear) are added to build the final model. R package: *polspline*.[156]
D. Decision trees – bagging[b]	Random Forest. Independent variables are partitioned (based on contiguous values) and stacked to build decision trees that are combined (ensemble) to create an aggregate “forest”. Random forest builds numerous trees in bootstrapped samples and generates an aggregate prediction by averaging across trees, thereby reducing over-fitting. R package: *ranger*.[57] Hyperparameters: max.depth = (2, 3, 4, 5), num.trees = (3000), mtry = (5, 10, 20), min.node.size = (300, 500, 1000, 1500).

eTable 5. Classifiers used in the Super Learner ensemble[a] (Continued)	
Algorithm	**Description**
II. Learners in the Super Learner library	
E. Decision trees - boosting	
Gradient Boosting Machine	GBMs build a sequential ensemble of shallow successive decision trees that iteratively learn the residuals from prior trees. This is a flexible method, where the number of trees, interaction depth, and shrinkage are leveraged to build flexible models. R package: *Catboost*.[157] Hyperparameters: Iterations=(500, 1000, 2000), learning_rate=(0.05, 0.03, 0.01), depth = (2, 3, 4, 5), min_data_in_leaf = (4, 16, 64, 256), max_leaves = (2, 4, 8 ,16, 32), grow_policy = ('Depthwise', 'Lossguide').
Extreme Gradient Boosting	A fast and efficient implementation of gradient boosting. R package: *xgboost*.[27] Hyperparameters: ntrees = (5000), max_depth = (2, 3, 4, 5), shrinkage = (0.1, 0.05, 0.01), gamma = (0, 4, 16, 64), minobspernode = (3, 9, 27, 81), colsample_bytree = (1, 0.8, 0.6), subsample = (1, 0.9, 0.8), colsample_bynode = (1, 0.9, 0.8).
F. Support Vector Machine	Support vector machines treat independent variables as dimensions in high dimensional space and attempts to identify the best hyperplane to separate the sample into classes (eg, cases and non-cases). The goal is to find the hyperplane with the maximum margin between the two closest points in space. SVM captures linear associations, but alternate kernels can be used to capture nonlinearities. R package *WeightSVM*. Hyperparameters: kernel = ('radial'), cost = (0.1, 1, 10, 100, 1000), gamma = (0.001, 0.0001, 0.00001).[158]
G. Bayesian Additive Regression Trees[b]	Fits Bayesian additive regression trees. R package: *dbarts*.[58] Hyperparameters: k = (1.0, 1.5, 2.0, 2.5, 3.0), ntree = (100, 200, 400).
H. Neural networks	Connections between predictors and the outcome are modeled as a network. The predictors affect the outcome through intermediate layers. Weights are assigned to connections. Neural networks capture interactions and non-linear associations but have low interpretability. R package: *nnet.* Hyperparameters: size = (2, 5, 10, 20), decay = (0, 0.1, 0.01, 0.001, 0.0001, 0.00001, 0.000001, 0.0000001)[159]
I. Mean	Arithmetic mean

[a]Hyperparameters: Default values were used unless otherwise noted.
[b]These algorithms with the hyperparamter settings below were also used to screen predictors as input for the learners: Elastic net: alpha = 0.9; Decision trees – bagging: ntree = 1000, splitrule = 'gini', importance = 'impurity_corrected'; Bayesian Additive Regression Trees: ntree = 2.

eTable 6. Distributions of Sociodemographic and Military Career Characteristics[a]

	Training sample (N=299,050)			Prospective validation sample (N=149,738)	
	%	(SE)		%	(SE)
I. Gender					
Male	93.9	(0.2)		93.2	(0.3)
Female	6.1	(0.2)		6.8	(0.3)
II. Age[b]	55.0	-		55.0	-
20-40	17.7	(0.3)		18.7	(0.4)
41-50	17.3	(0.3)		15.9	(0.4)
51-55	19.1	(0.3)		17.2	(0.4)
56-61	19.5	(0.3)		18.4	(0.4)
62+	26.4	(0.3)		29.9	(0.5)
III. Race/ethnicity					
Non-Hispanic white	62.8	(0.4)		61.5	(0.6)
Non-Hispanic black	24.2	(0.3)		23.2	(0.5)
Hispanic	7.7	(0.2)		7.8	(0.3)
Other	5.3	(0.2)		6.5	(0.3)
IV. Marital status					
Married	27.2	(0.3)		27.1	(0.5)
Divorced	39.6	(0.4)		39.3	(0.6)
Separated	7.4	(0.2)		6.3	(0.3)
Widowed	4.3	(0.2)		3.9	(0.2)
Never married	21.5	(0.3)		23.4	(0.5)
V. Patient income[c]					
No income	18.2	(0.3)		17.6	(0.4)
Low	13.6	(0.3)		13.1	(0.4)
Low-average	28.0	(0.3)		26.9	(0.5)
High-average	15.5	(0.3)		15.4	(0.4)
High	24.8	(0.3)		27.1	(0.5)
VI. Religion					
A. Christian	77.1	(0.3)		76.7	(0.5)
Baptist	27.8	(0.3)		26.2	(0.5)
Protestant	19.9	(0.3)		17.5	(0.4)
Roman Catholic	22.9	(0.3)		24.0	(0.5)
Other Christian	6.5	(0.2)		8.9	(0.3)
B. Non-Christian	4.5	(0.2)		5.4	(0.3)
C. None	18.4	(0.3)		18.0	(0.4)
VII. Census region					
Northeast	19.0	(0.3)		20.2	(0.5)
Midwest	21.6	(0.3)		21.4	(0.5)
South	41.5	(0.4)		39.6	(0.6)
West	17.9	(0.3)		18.8	(0.5)
VIII. Urbanicity					
Metro area with >1m population	48.7	(0.4)		51.6	(0.6)
Metro area with 250k - 1m population	24.7	(0.3)		23.5	(0.5)
Metro area with <250k population	10.5	(0.2)		10.5	(0.4)
Urban area with ≥20k population	6.3	(0.2)		5.9	(0.3)
Urban/rural area with <20k population	9.8	(0.2)		8.5	(0.3)
IX. Homelessness					
Currently homeless	10.9	(0.2)		14.0	(0.4)
Homeless in the past 12 months but not currently	18.8	(0.3)		20.7	(0.5)
Not homeless in the past 12 months	70.3	(0.3)		65.3	(0.5)

eTable 6. Distributions of socio-demographic and military career characteristics[a] (Continued)

	Training sample			Prospective validation sample	
	(N=299,050)			(N=149,738)	
	%	(SE)		%	(SE)
X. Last period of service					
Pre-Vietnam	7.7	(0.2)		7.9	(0.3)
Vietnam era	40.2	(0.4)		35.9	(0.6)
Post-Vietnam	23.2	(0.3)		23.7	(0.5)
Persian Gulf War	28.9	(0.3)		32.5	(0.5)
XI. High risk flag prior to admission					
Yes	6.2	(0.2)		5.9	(0.3)
No	93.8	(0.2)		94.1	(0.3)

Abbreviations: SE, standard error; 1m, 1 million; 250k, 250 thousand; 20k, 20 thousand.

[a]Psychiatric hospitalizations, not individuals, are the unit of analysis. This means that each patient who had multiple hospitalizations is represented multiple times in the sample.

[b]56 years median age and 46-62 inter-quartile range of age in the training sample; 55 years median age and 45-63 inter-quartile range of age in the prospective validation sample.

[c]Low income was defined as less than half the median among those with any income, low-average as between low and median, high-average as between the median and two times the median, and high as more than two times the median.

eTable 7. Prevalence of Suicide After Psychiatric Hospital Discharge in the Total, Training, and Prospective Validation Samples

	Study period (Jan. 1, 2010 - Dec. 31, 2013) (n = 448,788)		Training Sample (Jan. 1, 2010 – Sept 1, 2012) (n = 299,050)		Prospective Validation Sample (Sept. 2, 2012 - Dec. 31, 2013) (n = 149,738)	
Risk horizon	**Suicides per 100,000 hospitalizations**	**(n)**	**Suicides per 100,000 hospitalizations**	**(n)**	**Suicides per 100,000 hospitalizations**	**(n)**
12-months	280.9	(1,309)	306.3	(916)	262.5	(393)
6-months	173.0	(801)	185.9	(556)	163.6	(245)
3-months	104.6	(486)	113.4	(339)	98.2	(147)
1-month	51.8	(244)	57.8	(173)	47.4	(71)
1-week	21.5	(95)	20.7	(62)	22.0	(33)

Abbreviations: Jan., January; Dec., December; Sept., September.

eTable 8. Ten-Fold Cross-Validated AUC-ROC and AUC-PR of the Combined Model Over a Range of Risk Horizons in the Total Sample[a]

	AUC-ROC			AUC-PR_R	
Risk horizon	**Est**	**(SE)**		**Est**	**(SE)**
1 week	.824	(.019)		53.35	(8.14)
1 month	.823	(.013)		49.45	(9.41)
3 months	.838	(.009)		49.48	(7.89)
6 months	.851	(.007)		59.29	(4.75)
12 months	.883	(.006)		81.61	(4.02)

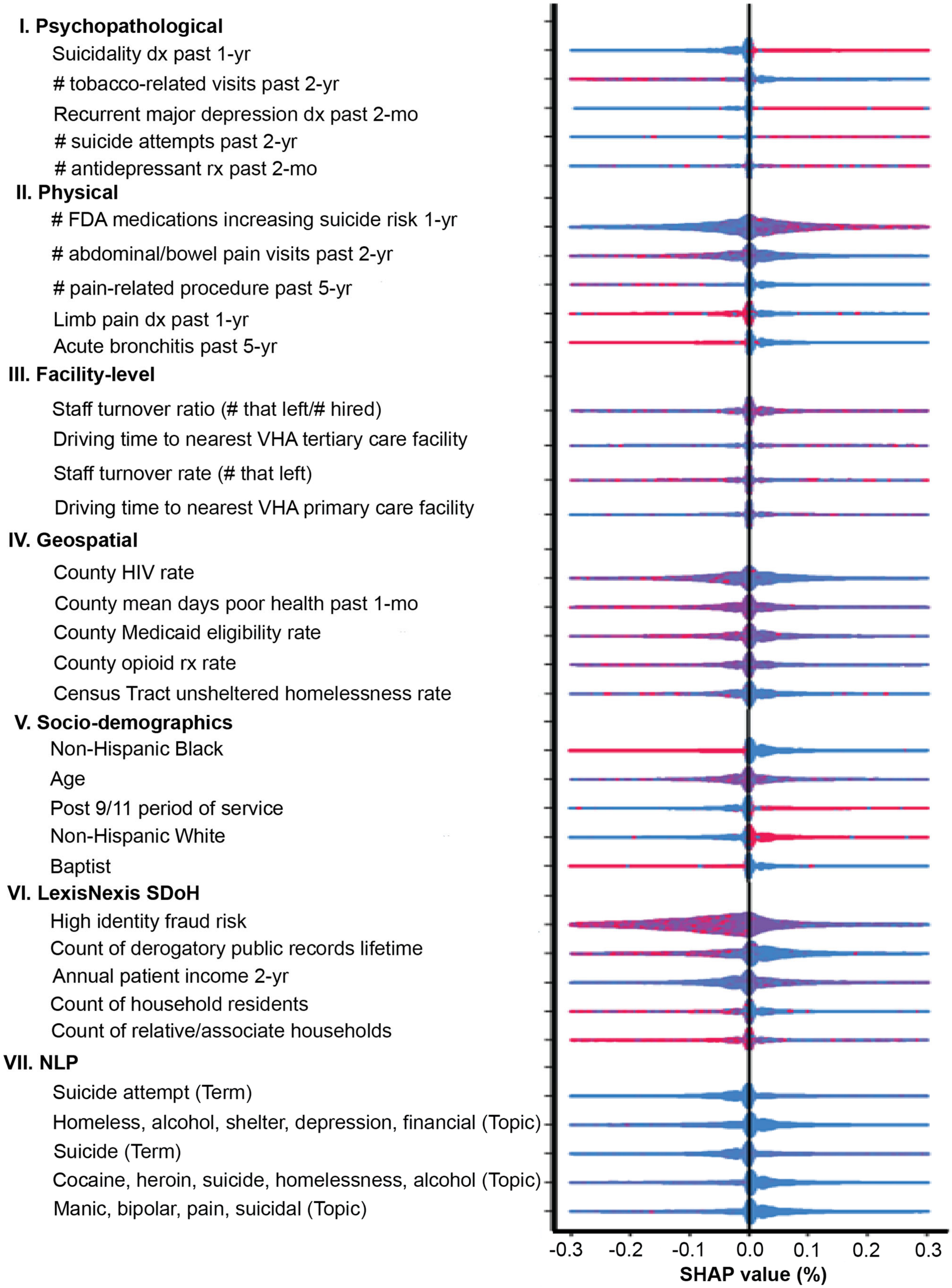
Abbreviations: AUC-ROC, area under the receiver operating characteristic curve; AUC-PR_R, area under the precision recall curve relative to observed suicide prevalence; Est, the estimated AUC-ROC or AUC-PR_R values over the risk horizon in the row; SE, Standard Error of Est.

[a]A 1:5 case-control sample was used for estimation and isotonic regression for calibration within folds.

eTable 9. Metalearner Weights for the Combined Model Estimated in the 10% Metalearner Weight Training Sample

Classifier	**Weight**
SVM: radial kernel, cost = 1,000, gamma = .001; 167 pairwise correlations <.8	0.618
XGBoost: max_depth = 5, eta = .1, gamma = 4, min_child_weight = 3, colsample_bytree = .8, Subsample = .8, colsample_bynode = 1; 100 ranger	0.348
XGBoost: max_depth = 4, eta = .05, gamma = 4, min_child_weight = 3, colsample_bytree = .6, Subsample = .8, colsample_bynode = 0.8; 100 ranger	0.030
NN: size = 20, decay = .01; 30 lasso	0.003
NN: size = 20, decay = .001; 30 lasso	0.001

eFigure. Bee swarm plot



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