Predictive modeling of housing instability and homelessness in the Veterans Health Administration

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Objective: To develop and test predictive models of housing instability and homelessness based on responses to a brief screening instrument administered throughout the Veterans Health Administration (VHA).

Data Sources/Study Setting: Electronic medical record data from 5.8 million Veterans who responded to the VHA's Homelessness Screening Clinical Reminder (HSCR) between October 2012 and September 2015.

Study Design: We randomly selected 80% of Veterans in our sample to develop predictive models. We evaluated the performance of both logistic regression and random forests—a machine learning algorithm—using the remaining 20% of cases.

Data Collection/Extraction Methods: Data were extracted from two sources: VHA's Corporate Data Warehouse and National Homeless Registry.

Principal Findings: Performance for all models was acceptable or better. Random forests models were more sensitive in predicting housing instability and homelessness than logistic regression, but less specific in predicting housing instability. Rates of positive screens for both outcomes were highest among Veterans in the top strata of model-predicted risk.

Conclusions: Predictive models based on medical record data can identify Veterans likely to report housing instability and homelessness, making the HSCR screening process more efficient and informing new engagement strategies. Our findings have implications for similar instruments in other health care systems.

KEYWORDS

homelessness, veterans

1 | INTRODUCTION

Housing instability and especially homelessness, which is an acute form of housing instability, are associated with a range of adverse health outcomes^{1,2} and increased costs for health care systems.³⁻⁵ This knowledge has led to growing recognition of housing as an important social determinant of health⁶ and a corresponding increase in efforts of health care systems to address housing instability and homelessness, ranging from interventions in clinical settings,⁷ to new care delivery,⁸ and financing mechanisms.⁹

From a practical standpoint, efforts to address housing instability within the health care system rely on the accurate identification

of those who are, or are at risk of, experiencing housing instability. Accurate identification can lead to more efficient targeting of interventions to prevent housing instability or to mitigate the potential ill effects of continued housing instability. The development and testing of approaches to achieve this goal is a growing area of inquiry: several recent studies have tested methods that rely on data obtained from patients' medical records to identify persons at risk of or experiencing homelessness using a variety of indicators including diagnosis codes,¹⁰ address information,^{11,12} and free text notes.¹³⁻¹⁵

An alternative approach relies on self-reported information about housing status collected through the use of screening tools administered to patients in clinical settings.¹⁶⁻¹⁹ The U.S. Department of

Veterans Affairs' (VA) Homelessness Screening Clinical Reminder (HSCR) is one such screening instrument that has been deployed on a wide scale. Since the beginning of Federal Fiscal Year (FFY) 2013, the HSCR has been included in Veterans' medical records as a clinical reminder to be administered to all Veterans who access outpatient care through the Veterans Health Administration (VHA).

The HSCR is part of an ambitious primary prevention approach to address housing instability; however, the existence of the HSCR alone is insufficient to improve housing stability. Prior studies have documented the challenges of effectively using information from self-reported screening instruments on social determinants of health such as housing instability.²⁰⁻²⁴ These challenges fall into two broad categories: (a) determining how to resolve the logistical, resource, and workload issues associated with the collection of information about housing instability and other social factors from patients; and (b) optimizing procedures for taking action on such information. With respect to the first set of challenges, evidence suggests that workload concerns are barriers to the effective implementation of screening tools. For example, clinicians may perceive that screening instruments or clinical reminders like the HSCR do not apply to patients²⁵ and may experience a phenomenon known as "reminder fatigue" wherein an increasing number of clinical reminders for providers to complete leads to decreasing adherence to intended screening protocols.²⁶ With respect to the second set of challenges, taking action on information about housing instability and other social factors requires that this information is readily available to health care team members when they are making decisions about how to tailor care, referrals, and follow-up to patient needs.²² Acting on information about housing instability also requires knowledge about what resources are available to address needs and how to connect people with those resources.²³

Knowledge about which Veterans are at high risk of screening positive for housing instability could inform refinements to the implementation of the HSCR, ensuring that it is administered in a way that efficiently uses clinician and system resources. Such knowledge could also help establish standardized procedures to use information about Veterans' risk of housing instability to engage them with appropriate services. In the present study, we used measures obtained from Veterans' electronic medical records to develop and test predictive models of their risk of screening positive for housing instability or homelessness when responding to the HSCR. We evaluated the performance of both a conventional regression modeling approach and a widely used machine learning algorithm to assess whether the latter approach resulted in better performance. Finally, we examined the concentration of risk of positive screening in specific strata of Veteran respondents to better understand the potential development of more targeted screening and intervention approaches, stratified by risk.

2 | METHODS

2.1 | Sample

We identified the study sample using data collected from Veteran respondents to the HSCR. The two questions that comprise the HSCR are:

1. In the past 2 months, have you been living in stable housing that you own, rent, or stay in as part of a household?
2. Are you worried or concerned that in the next 2 months you may NOT have stable housing that you own, rent, or stay in as part of a household?

Veterans who respond either negatively to the first question or affirmatively to the second are asked a follow-up question about where they have lived for the majority of the previous 2 months (an apartment, house, or room that one rents or owns, either with or without a subsidy; with family or friends; in a hotel or motel; in an institutional setting, such as a hospital, short-term rehabilitation center, treatment program, jail/prison; in an emergency shelter or other homeless residential program; on the street, in a vehicle, abandoned building, or anywhere outside). Veterans who screen positive are also asked if they would like a referral to discuss their living situation further. The HSCR is administered on an annual basis to all Veterans who access VA outpatient care. Veterans who screen positive are readministered the questions every 6 months.

The study sample included all 5 852 791 Veterans who were administered the HSCR for the first time between October 1, 2012 and September 30, 2015. A total of 21 470 Veterans did not complete the HSCR because they were already involved in a VHA Homeless Program or were receiving long-term or palliative care; these Veterans were dropped from the sample. An additional 2551 Veterans had missing responses to the HSCR and were excluded. Consistent with the HSCR protocol, we eliminated an additional 44 042 Veterans who had a record of VHA Homeless Program use in the prior 6 months. We excluded an additional 36 Veterans who were missing information on some of the demographic variables, resulting in a final sample of 5 784 692 Veterans.

2.2 | Measures

We constructed two outcome measures based on responses to the HSCR. First, we created a dichotomous measure of whether Veterans reported any housing instability, defined as responding either negatively to the first question of the HSCR or positively to the second question. Second, we constructed a measure of homelessness, which included Veterans who reported that they had lived for the majority of the previous 2 months in an institutional setting, an emergency shelter or other homeless residential program, or anywhere outside. This measure aligns with the Department of Housing and Urban Development's official statutory criteria for "literal homelessness,"²⁷ which does not include persons who are doubled-up with family or friends.

We based our selection of predictor variables on prior epidemiological research identifying risk factors for homelessness among both Veterans and non-Veterans²⁸⁻³² as well as on prior studies that have explicitly sought to develop predictive models of homelessness.^{33,34} These measures come from two sources: Veterans' electronic medical records, which are available in the VA's Corporate Data Warehouse (CDW) and from the VA's National Homeless Registry, which tracks utilization of VHA Homeless Programs. We

included a set of demographic variables related to Veterans' military service, eligibility for VHA health care based on VHA's Enrollment Priority Groups, and use of VHA inpatient and outpatient services over the 18 months prior to the date of first response to the HSCR. We also identified behavioral and chronic health diagnoses by applying the algorithm developed by Elixhauser and colleagues³⁵ to International Classification of Diseases-9th Revision (ICD-9) codes in Veterans' medical records for service episodes that occurred in the 18 months prior to screening. Finally, we assessed whether Veterans had any contact with a VHA Homeless Program at any point in the 18 months prior responding to the HSCR. (See Table 1 for a list of independent variables.)

2.3 | Analysis

We used stratified random sampling, based on whether Veterans reported any housing instability, to assign 80% of individuals in the sample to a development sample, which was used to develop the predictive models for each outcome. The remaining 20% served as a validation sample to evaluate model performance. Stratification ensured a relatively equal proportion of Veterans reporting housing instability and homelessness in both the development and validation samples.

We tested two classification methods for predicting each of the outcome measures based on the full set of predictor variables. First, we employed multivariable binary logistic regression. We applied parameter estimates from the logistic regression model estimated using the development sample to generate predicted probabilities for each outcome for individuals in the validation sample. We evaluated model performance using several metrics including area under the receiver operating characteristic curve (AUROC), sensitivity (true positive rate) and specificity (true negative rate). Because of the low rate of positive responses to the HSCR indicating housing instability and homelessness, we also examined a metric that is sensitive to the underlying prevalence of an outcome in the population of interest. Specifically, we used positive predictive value, which measures true positives as a proportion of all model predicted positives. Holding AUROC constant, positive predictive value will be lower as the baseline prevalence of an outcome in a population decreases.

We also ranked Veterans in the validation sample on the basis of their predicted probabilities for each outcome and classified them into risk strata comprised of persons in the top 0.5%, 1%, 5%, 10%, 25% 50%, and 75% of the predicted risk distribution. We selected these tiers based on prior research that found them to be operationally useful for the development of a predictive model of suicide risk in the VHA.^{36,37}

We initially estimated logistic regression models using all individuals in the development sample. However, the small proportion of cases reporting housing instability and homelessness (1.8% and 0.18%, respectively) resulted in models that had near perfect specificity but extremely poor sensitivity. We then used an approach known as downsampling³⁸ to balance the outcome class membership of the development sample by retaining all individuals who screened positive and randomly selecting an equal number of cases who screened negative. All cases were

retained in the validation sample to assess model performance on a dataset that is likely to align with real world conditions. Results are based on the models estimated using the downsampled development sample.

We also tested a machine learning algorithm known as random forests to assess its performance relative to logistic regression. The random forests method develops predictions of outcome class membership by combining the results from a large number—or a “forest”—of classification tree models. Classification tree models work through a recursive partitioning of the complete set of predictors into a simpler number of regions, with the predicted outcome for a given observation determined by the most commonly occurring outcome value of all observations in the region in which a given observation falls.³⁹ Classification tree models search through all possible values of all possible predictors to identify specific predictors and distinct split values for the predictor that results in a separation of the data into two separate groups, minimizing heterogeneity with respect to the outcome of interest. In the current context, a classification tree might initially identify a split of the data into those age 50 and younger and those older than 50 as the “best” break point in that, relative to all other possible split points of all other variables, this split minimizes heterogeneity between observations in each of these two subgroups with respect to housing instability. This process would then repeat itself to identify the next best predictor and cut point to split the existing two regions into three regions, and so on until some stopping rule is reached, such as requiring each region to have no more than 10 observations. Classification trees have two notable advantages to regression-based methods. First, classification trees do not assume that the relationship between the predictor variables and the outcome follows any specific functional form. Second, by recursively partitioning the data based on the set of independent variables, classification trees automatically account for interaction effects between variables, whereas interactions need to be specified *a priori* in regression-based models.

Random forests create a large number of classification trees by using a correspondingly large number of bootstrapped samples from the data (ie, samples randomly selected with replacement from the original sample). However, each classification tree is built using only a random subset of predictors, rather than the full set. By using only a subset of predictors, predictions generated across trees are independent. Random forests models must be “tuned” to select the optimal number of predictor variables to be considered when growing each classification tree. In the present study, we tuned the random forests models on the training data using an approach known as five-fold cross validation,³⁹ and used AUROC in the model tuning process to select the optimal value for the tuning parameter. As with the logistic regression models, we used downsampling to deal with outcome class imbalance when training the random forests model and evaluated model performance using the full validation sample.

Our main analyses included all predictor variables; however, given that prior homelessness is known to be a strong predictor of future homelessness, we estimated an additional set of models that did not include prior use of VHA Homeless Programs. We also conducted separate sets of analyses for the following specific subgroups of interest: female Veterans, Veterans of Operations Enduring and Iraqi Freedom

TABLE 1 Descriptive characteristics of study sample

	Negative ^a (%)	Any Housing Instability ^a (%)	Homelessness ^a (%)	Total (%)
N	5 680 616 (98.2%)	104 076 (1.8%)	10 134 (0.2%)	5 784 692
Gender				
Female	7.1	10.2	4.5	7.2
Male	92.9	89.8	95.5	92.8
Age (mean)	61.2	50.9	53.8	61.1
Ethnicity				
Hispanic	5.7	7.8	6.8	5.7
Not Hispanic	88.5	87.9	88.6	88.5
Unknown	5.8	4.3	4.6	5.8
Race				
White	76.4	60.2	60.6	76.1
Black	15.4	29.1	29.3	15.7
American Indian or Alaskan Native	0.7	1.3	1.2	0.7
Asian	0.9	1	0.7	0.9
Native Hawaiian/Pacific Islander	0.7	1	1	0.8
Other	0.1	0.1	0.1	0.1
Unknown/missing	5.8	7.3	7.1	5.8
OEF/OIF service	11.1	16.7	8	11.2
Marital status				
Divorced	21.1	37.1	44.5	21.4
Married	56.9	26.6	11.1	56.3
Separated	2.9	7.9	8.3	3
Single/never married	12	24.3	31.7	12.2
Widow	6.4	3.5	3.7	6.4
Unknown	0.6	0.6	0.6	0.6
VA enrollment priority group				
Service-connected disability >50%	29.9	28.2	17.8	29.9
Service-connected disability <50%	22.7	21.9	19.6	22.7
No service-connected disability	44	44	51.7	44
No service-connected disability, VA Pension	1.8	4.9	9.5	1.9
Other	1.5	1	1.4	1.5
Rural screening location	17.6	12.8	9.8	17.5
Clinic location of screening				
Primary care	88.9	75.9	69.9	88.6
Behavioral health clinic	6.3	14.5	14.8	6.5
Drug/alcohol treatment clinic	0.2	1.6	2.5	0.3
Emergency department	0.4	0.8	2	0.4
HUD-VA supportive housing	0	0.2	0.3	0
Medical specialty clinic	3.4	3.3	3.3	3.4
Other	0.7	3.7	7.1	0.8
Region				
West	20.8	31.6	43.7	21
South	26.2	22	18.7	26.1

(Continues)

TABLE 1 (Continued)

	Negative ^a (%)	Any Housing Instability ^a (%)	Homelessness ^a (%)	Total (%)
Midwest	36.4	31.6	25.3	36.3
Northeast	16.6	14.8	12.3	16.5
Branch of service				
Army	53	54	52.1	53
Navy	19.7	20.2	21.5	19.8
Air force	14.7	11.4	11.4	14.6
Marine corps	11	13	13.4	11
Coast guard	0.9	0.9	1.1	0.9
Other	0.1	0.1	0.1	0.1
Missing/unknown	0.6	0.5	0.4	0.6
History of combat	10.3	8.5	5.6	10.3
Services use				
VHA homeless program use in prior 18 months	0.2	1.4	3.5	0.2
Assessment for VHA Homeless Program in prior 18 months	0.1	0.7	1.8	0.1
Inpatient medical days in prior 18 months (mean)	0.6	0.8	1.5	0.6
Inpatient mental health days in prior 18 months (mean)	0.2	0.9	2.2	0.2
Inpatient substance abuse days in prior 18 months (mean)	0	0.3	0.6	0.1
Outpatient primary care visits in prior 18 months (mean)	2.6	2.5	2.5	2.6
Outpatient medical visits in prior 18 months (mean)	10.7	10.2	10.5	10.7
Outpatient mental health visits in prior 18 months (mean)	2.3	4.7	6	2.4
Outpatient substance abuse visits in prior 18 months (mean)	0.5	2	3.7	0.5
Diagnoses				
Psychoses	5.6	11.4	11.5	5.7
Depression	8.1	14.7	14	8.2
Schizophrenia	3.2	4.7	7.5	3.2
Alcohol abuse	3.5	9.9	15.8	3.6
Drug abuse	2.1	8.5	14.4	2.3
Post-traumatic stress disorder	8.3	11.3	9.1	8.4
Suicide	0.7	2.8	5	0.7
Any chronic health condition	41.7	33	31.3	41.5
Congestive heart failure	2.1	1.5	1.6	2.1
Chronic pulmonary disease ^b	5.6	4.8	5.7	5.6
Hypertension	28.9	21.7	20.1	28.8
Diabetes	16	10.7	8.5	15.9
Neurological disorder ^b	2.5	2.2	2.6	2.5
Renal failure	3	1.6	1.5	2.9

(Continues)

TABLE 1 (Continued)

	Negative ^a (%)	Any Housing Instability ^a (%)	Homelessness ^a (%)	Total (%)
Liver disease	1.4	2.7	4.2	1.4
HIV/AIDS	0.3	0.6	0.7	0.3
Metastatic tumor ^b	0.3	0.2	0.3	0.3
Solid tumor without metastasis	4.1	2.2	2	4
Rheumatoid arthritis	0.8	0.5	0.4	0.8
Obesity	6.3	5.9	4.4	6.3
Weight loss	0.6	0.8	1.2	0.6
Traumatic brain injury	0.2	0.3	0.4	0.2

Notes: All comparisons (any positive vs negative/homeless vs not homeless) are statistically significant at the $P < 0.001$ level unless otherwise noted. OEF/OIF Service = Veterans of Operations Enduring and Iraqi Freedom (OEF/OIF).

^aThe sum of the three categories do not sum to total because Veterans identified as screening positive for homelessness constitute a subset of all Veterans who screen positive for any housing instability.

^bHomeless vs not homeless comparison not significant at $P < 0.05$ level.

(OEF/OIF), and older Veterans (age 55 years and older). The first two of these groups are younger and will comprise increasingly large shares of the Veteran population⁴⁰ and the third group is likely to comprise a larger share of the homeless Veteran population due to an age cohort effect in the homeless Veteran population.⁴¹ All analyses were conducted using the R environment for statistical computing;⁴² random forests models were estimated using the caret package,⁴³ which was designed specifically for the development of predictive models in R.

3 | RESULTS

Table 1 shows the characteristics of the full study sample. There were pronounced differences between those who screened positive for any housing instability or homelessness and those who screened negative with respect to age, race, marital status, and recent use of VHA Homeless Programs as well as inpatient and outpatient care related to behavioral health. Those who screened positive for housing instability or homelessness had markedly higher rates of diagnoses for psychoses, depression, alcohol and drug abuse, liver disease, and HIV/AIDS. There were no substantively meaningful differences between Veterans in the development and validation samples (see Table S1).

3.1 | Model performance

Table 2 summarizes the performance of the models predicting housing instability and homelessness. AUROC values for all models were acceptable to excellent by conventional guidelines,⁴⁴ with the random forests models performing better than the logistic regression models for both the housing instability (85.4 vs 78.3) and homeless (91.6 vs 87.1) outcomes. For both outcomes, the random forests models had higher sensitivity, correctly identifying more Veterans who screened positive. However, they had lower specificity, identifying

more false positives. Positive predictive value was quite low in absolute terms for all models, suggesting that all models identified a large number of false positive for every true positive identified. Results of the models that excluded VHA Homeless Program predictors were highly similar to the models that included them.

Applying the models to the validation sample resulted in a noticeable decline in performance for the random forests models, but not the logistic regression models, suggesting a problem of overfitting in the development sample for the random forests models. Nonetheless, the pattern of findings with respect to model performance was similar in the validation sample as compared with the development sample. The random forests models performed slightly better with respect to AUROC for both the housing instability (79.5 vs 78.4) and homelessness (88.2 vs 87.2) outcomes. Regardless of the model, these AUROC values are in the acceptable range for the housing instability outcome and the excellent range for the homelessness outcome by conventional guidelines.

The random forests models were more sensitive than the logistic regression models for the housing instability (78.5% vs 72.6%) and homelessness (83.4% vs 82.1%) outcomes, and more specific for the homelessness outcome (77.7 vs 77.6), but less specific for the housing instability outcome (67.4% vs 70.3%). Assuming the baseline prevalence of housing instability is held constant at 1.8%, the sensitivity-specificity tradeoff for the housing instability outcome measure would translate into an additional 106 Veterans correctly identified per 100 000 Veterans screened at the expense of an additional 2848 false negatives.

The positive predictive value for the random forests and logistic regression models were highly similar for both outcomes. For both types of models, the positive predictive values suggest that performance was about 2.4 and 3.3 times better than what would be expected based on chance alone for the housing instability and homelessness outcomes respectively. Nonetheless, these values indicate that for each Veteran correctly identified as screening

TABLE 2 Summary of performance of predictive models of any housing instability and homelessness

	Any housing instability				Homelessness			
	AUROC	Sensitivity	Specificity	PPV	AUROC	Sensitivity	Specificity	PPV
Development sample								
All veterans								
Logistic Regression	78.3	72.4	70.3	4.3	87.1	81.8	77.0	0.6
Random Forests	85.4	86.2	67.6	4.6	91.6	89.9	76.7	0.7
All Veterans-No VA homeless program predictors								
Logistic Regression	78.2	72.5	70.1	4.3	86.8	81.7	76.5	0.6
Random Forests	85.4	86.2	67.5	4.6	93.2	93.1	77.0	0.7
Validation sample								
All Veterans								
Logistic Regression	78.4	72.6	70.3	4.3	87.5	82.1	77.6	0.6
Random Forests	79.5	78.5	67.4	4.2	88.2	83.4	77.7	0.7
All Veterans-No VA homeless program predictors								
Logistic Regression	78.3	72.6	70.1	4.3	87.2	81.9	76.8	0.6
Random Forests	79.5	78.6	67.2	4.2	88.2	83.5	77.5	0.6

AUROC, Area under the receiver operating characteristic curve; PPV, Positive predictive value.

positive for housing instability there would be 23 false positives; for homelessness there would be 160 false positives for every Veteran correctly identified by the models as screening positive for homelessness. Here again, excluding VHA Homeless Program predictors had little impact on model performance in the validation sample.

3.2 | Concentration of risk

Table 3 summarizes concentration of risk of positive screening for any housing instability and homelessness among Veterans in the validation sample and based on the models that included all predictors. There was strong risk concentration in the top risk strata, with the logistic regression models resulting in more concentrated risk in the upper risk tiers than the random forests models. Specifically, Veterans identified as being in the top 0.5% in terms of their model predicted risk accounting for between 3% and 4% of all those who reported any housing instability (or roughly 5.7-7.7 times what would be expected by chance alone), and between 8% and 13% of all those who reported homelessness (or roughly 15.4-25.6 times what would be expected by chance alone). Among those in the top 0.5%, rates of positive screening for housing instability were above 10% for both the logistic regression and random forests models, relative to 1.8% for the entire sample. For the homelessness outcome, rates of positive screening for Veterans in this risk tier were 4.5% and 2.7% for the logistic and random forest model respectively. Both of these rates far exceeded the 0.2% positive screening rate for the entire

sample. High concentration of risk persisted in lower tiers as well, although there was less difference in risk concentration between the logistic regression and random forests models than in the upper tiers. Regardless of the model, those in the top 25% accounted for about two-thirds of those reporting any housing instability and about 85% of those reporting homelessness, and those in the top 50% accounted for about 90% of all those reporting housing instability and 96% of those reporting homelessness.

The results of the analysis for the female, OEF/OIF, and older Veterans subgroups yielded results that were generally similar to those for the full sample, with slightly better performance observed in the models that only included older Veterans relative to the models based on the full sample and those that only included female and OEF/OIF Veterans respectively. (See Appendix Table S2 and Appendix Figure S1.)

4 | DISCUSSION

This study demonstrated that predictive models based on medical record data can effectively identify Veterans who are at an elevated risk of reporting housing instability or homelessness when responding to a brief screening instrument administered in a clinical setting. Our models were generally more sensitive than specific, indicating better performance in correctly identifying Veterans reporting housing instability or homelessness than in correctly identifying Veterans not reporting these experiences. In this context, higher sensitivity may be more desirable than high specificity if the goal is to correctly

TABLE 3 Concentration of risk of screening positive for any housing instability and homelessness among Veterans in validation sample, by tier of predicted probability and model

Tier of predicted probability, %	Any housing instability						Homelessness					
	Logistic regression			Random forests			Logistic regression			Random forests		
	% of all positive screens	Ratio of observed to expected positive screens	% with positive screen	% of all positive screens	Ratio of observed to expected positive screens	% with positive screen	% of all positive screens	Ratio of observed to expected positive screens	% with positive screen	% of all positive screens	Ratio of observed to expected positive screens	% with positive screen
0.5	4.2	7.7	15	2.9	5.7	10.3	12.8	25.6	4.5	7.7	15.4	2.7
1	6.9	6.6	12.5	5.0	5.0	9.0	18.9	18.9	3.3	14.4	14.4	2.5
5	22.0	4.3	7.9	20.5	4.1	7.3	41.9	8.4	1.5	45.4	9.1	1.6
10	36.0	3.6	6.5	37.5	3.8	6.7	59.2	5.9	1.0	62.8	6.3	1.1
25	64.9	2.6	4.7	68.4	2.7	4.9	84.5	3.4	0.6	85.5	3.4	0.6
50	88.9	1.8	3.2	90.2	1.8	3.2	96.3	1.9	0.3	96.5	1.9	0.3
75	97.5	1.3	2.3	97.6	1.3	2.3	99.1	1.3	0.2	99.4	1.3	0.2
100	100	1.0	1.8	100	1.0	1.8	100	1.0	0.2	100	1.0	0.2

identify as many individuals experiencing a rare phenomenon such as homelessness.

Models predicting homelessness were both more sensitive and more specific than models predicting any housing instability. This finding is consistent with an understanding of homelessness as a distinct and acute form of housing instability and suggests that risk factors for homelessness are more pronounced in electronic medical records. We also found a strong concentration of the risk of screening positive for housing instability and homelessness in the top risk tiers, with Veterans in the top half of the risk distribution accounting for 90% or more of all Veterans who screened positive for these outcomes.

When comparing model approaches, the random forests models performed slightly better than the logistic regression models by some performance metrics, but there were not substantial differences between the two model types overall. This modest improvement in the performance of random forests relative to logistic regression parallels findings from a study that compared the performance of these two models in terms of their ability to predict reentry into the homeless assistance system.⁴⁵

Our models yielded low positive predictive values, which highlight the inherent challenges associated with developing predictive models to identify a rare outcome. For each person correctly identified as reporting housing instability or homelessness, our models would identify 23 and 160 false positives, respectively. Such problems are common in developing predictive models based on data with severely imbalanced outcomes and have been noted as a significant challenge for the field of predictive modeling.⁴⁶

Our findings have implications for refining the administration of the HSCR, and for guiding action in instances when Veterans are identified as being at high risk of reporting housing instability or homelessness. First, our finding that risk of screening positive is strongly concentrated in the top risk tiers suggests that developing a tiered strategy for administering the HSCR could reduce reminder fatigue and make more efficient use of system resources. One refinement would be to administer the HSCR only to those Veterans predicted by our model to be in high-risk strata. Our findings suggest that the number of Veterans screened could be cut in half while still capturing upwards of 90% of those screening positive for housing instability or homelessness. This strategy would miss fewer than 10% of those who would have otherwise screened positive. Such a targeted approach would also improve screening yield. Under the current universal implementation of the HSCR, roughly 1 in every 55 patients screened reports housing instability. Targeting screening to those in the top 50% of the model-predicted risk distribution would result in roughly 1 in every 31 patients reporting housing instability, nearly doubling screener yield.

Recent research has suggested that exactly this approach—limiting screening to only a subset of patients and using information in electronic medical records to target this subset—should be given consideration as a potential strategy for minimizing the workload burden placed on health care teams when administering screenings for social determinants of health.²³ In the aggregate, this approach would greatly reduce the amount of clinician time dedicated to the

HSCR given the size of the VHA patient population. Such a reduction is a nontrivial issue in the VHA system, where clinicians may be asked to complete many screening instruments, including for other social factors such as food insecurity⁴⁷ and intimate partner violence.⁴⁸

An alternative approach might be to maintain universal administration of the HSCR and institute certain risk-stratified modifications, such as screening those in lower risk strata less frequently and those in higher risk strata more frequently. This would result in more efficient use of clinician and system resources while addressing concerns about the unintended consequences of targeted screening for social determinants of health, such as missing patients who experience a sudden change in risk or the possible stigmatization that may be associated with screening only certain persons.²⁰ We believe that both a targeted and modified universal approach would be reasonable, but also argue that decisions about changing the HSCR should be made in a deliberative manner, involving input from clinicians, patients, and other stakeholders. As an extension of the current study, we conducted qualitative interviews with both patients and clinicians who have administered or responded to the HSCR. Findings from these interviews will inform refinements to the implementation of the HSCR and revision of our set of predictor variables to improve the accuracy of our models.

Our findings could also be used to inform new procedures to help engage high-risk Veterans with appropriate services. At present, the HSCR only triggers potential engagement with specialized homeless program or social work services at the time when it is administered. This could change, however, if information about model-predicted risk of reporting housing instability or homelessness were to be embedded in Veterans' electronic medical record and clinicians were alerted when a patient is identified as being at a high risk. Our models could be used to generate and periodically update this risk score even for Veterans who are not scheduled to complete the HSCR during a given service episode. Such information could inform clinicians' actions about how to tailor care and referrals. Proactive efforts may be made to engage Veterans in the very highest-risk tiers of housing instability or homelessness, even before they are screened. For example, VA social work and homeless program staff could conduct targeted outreach efforts to high-risk Veterans to conduct more in-depth assessments and facilitate linkages to services. In the ideal case, automated systems might trigger action on this information, perhaps by prompting clinicians to make referrals to resources available to address housing instability, or even by automating the referral itself.²² From a broader perspective, targeting interventions to Veterans identified as being at high risk even before they are screened has the potential of preventing housing instability or homelessness before they occur.

Implications from our study extend beyond the VA system. Other health care systems could adapt our model using their own medical records to identify persons who may be at high risk of housing instability or homelessness, and use this information to

tailor screening approaches or other interventions. The VA is a unique system that offers a full spectrum of health, behavioral health, rehabilitation, social work, and specialized homeless assistance services; other health care systems may not have access to the complete set of predictors that we included in our models. However, the inclusion of a predictor for prior use of VHA Homeless programs—the type of predictor that other health care systems are unlikely to be able to obtain—had little impact on the performance of our models, which suggests that our approach may be generalizable to other settings. Adapting our model and testing its performance in other settings is an important goal for future research.

This study has several limitations. First, we were only able to assess predictors available in Veterans' electronic medical records. Although this allowed us to include many known correlates of homelessness, we did not have access to other potentially important predictors, such as adverse childhood experiences, incarceration history, or recent income shocks. Future research incorporating these predictors could improve model performance. Second, because our models are based on VA electronic medical record data and include predictors capturing Veterans' use of VA services in the prior 18 months, they may be inaccurate at identifying Veterans who have only recently initiated care in the VA system. Finally, the HSCR asks Veterans about their housing status over a short (2 months) time period; consequently, our models provide little information about the predicted risk of housing instability or homelessness over a more extended timeframe.

There is growing interest in screening for and addressing housing instability within health care systems. Yet, the success of efforts to do so depends on the resolution of the key questions of how to collect information about housing instability from patients and how to intervene to address identified needs. Findings from this study demonstrate how predictive models based on electronic medical record data might be of use to health care systems in addressing these questions. As we have argued, this information might be used by health care systems to tailor their screening and intervention procedures; any application of information from these models should be the product of careful deliberation and rigorously evaluated once implemented.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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