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# Predictive risk modeling to identify homeless clients at risk for prioritizing services using routinely collected data

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**ABSTRACT**
For most homelessness service providers, the number of clients who are eligible for long-term housing outstrips the availability. This study uses a cohort of housing assessments taken from a mid-size county in the US and machine learning methods to train a Predictive Risk Model (PRM) that identifies clients who would experience multiple adversities in the future. The PRM outperforms the Vulnerability Index-Service Prioritization Decision Assistance Tool (VI-SPDAT) in flagging clients at the greatest risk of adversities. The proposed method can be readily used by any Continuum of Care (CoC) that holds electronic housing assessments and service records.

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**KEYWORDS**
Homelessness; predictive risk model; homelessness assessment; triage tool; prioritizing persons experiencing homelessness; VI-SPDAT

## Introduction

Homelessness in the US has grown by 3% in 2019 compared to the previous year (The U.S. Department of Housing and Urban Development (HUD), 2020), and with the impact of the Covid-19 pandemic and the associated economic downturn, it is highly likely there will be a surge in homelessness in the coming years.

The U.S. Department of Housing and Urban Development funds non-profit providers, and state and local governments to support homeless individuals and families with emergency, transitional, and long-term housing services through the McKinney-Vento Act as amended by the Homeless Emergency Assistance and Rapid Transition to Housing (HEARTH) (HEARTH Act 2009). These housing services are scarce yet in high demand, so HUD has required communities through their local Continuum of Care funding intermediaries (CoCs) to establish "Coordinated Entry Systems" (CES) that could theoretically rationalize the process of client program assignment (The U.S. Department of Housing and Urban

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Development (HUD), 2015a). HUD encourages communities to prioritize applicants who have the highest need for these services by using a screening or assessment instrument (The U.S. Department of Housing and Urban Development (HUD), 2015a, 2015b). Such an assessment should be capable of identifying and prioritizing the factors associated with the greatest risk for long-term homelessness or other undesirable health and social outcomes (The U.S. Department of Housing and Urban Development (HUD), 2015a).

Studies have identified diverse risk factors associated with homelessness, such as an inability to afford a house or pay rent (Burt, Pearson, & Montgomery, 2005; Leopold, Getsinger, Blumenthal, Abazajjan, & Jordan, 2015); a history of incarceration (Couloute, 2018; Gowan, 2002); being a military veteran (Ackerman, Porter, & Sullivan, 2020; Perl, 2015); domestic violence (Baker, Billhardt, Warren, Rollins, & Glass, 2010; Petering, Rice, Rhoades, & Winetrobe, 2014); mental health issues (Burt et al., 2005; Folsom et al., 2005); exposure to childhood maltreatment (Edalati, Krausz, & Schütz, 2016; Mar, Linden, Torchalla, Li, & Krausz, 2014); physical health problems (Zerger, Strehlow, & Gundlapalli, 2008); substance use problems (Burt et al., 2005; Thompson, Wall, Greenstein, Grant, & Hasin, 2013); and certain demographic characteristics (Smith, Flores, Lin, & Markovic, 2005).

Some of the above risk factors and previous research on housing instability indicators have formed the basis for the development of prioritization tools – of which the Vulnerability Index-Service Prioritization Decision Assistance Tool (VI-SPDAT)[1] has been the most popular (OrgCode Consulting Inc. & Community Solutions, 2015a, 2015b, 2015c). The tool vendors claim that it is used in over 1,000 communities across the US, Canada, and Australia.

Being homeless can cause consequent adversities including a deterioration in mental and physical health leading to hospital emergency room and inpatient admission (Fazel, Geddes, & Kushel, 2014; Tadros, Layman, Brewer, & Davis, 2016); substance use disorder (Narendrof, 2017; Schutz, 2016); criminal justice involvement (Gonzalez et al., 2018; Kushel, Hahn, Evans, Bangsberg, & Moss, 2005); and excessive gambling (Nower, Eyrich-Garg, Pollio, & North, 2015). Children experiencing homelessness can suffer lower achievement in education (Walker-Dalhouse & Risko, 2008). Quite apart from these ongoing harmful effects, chronic homelessness (Burt et al., 2005; Kuhn & Culhane, 1998) can be exacerbated by these adversities. For example, poor mental and physical health can have detrimental effects on labor market participation, leading to homelessness, but is also exacerbated by homelessness. This is to say that a homeless assessment instrument should consider not only a client's exposure to the causes of homelessness like mental health challenges but also future vulnerability to the harms associated with homelessness, such as the risk of future mental health crises.

To establish a better homeless service prioritization method, several studies have followed data driven approaches to recognize future vulnerabilities. Shinn, Greer, Bainbridge, Kwon, and Zuiderveen (2013) used administrative data on clients of the New York city homelessness system to develop a predictive risk model designed to identify clients who were most likely to enter shelter. Clients' demographics, human capital, housing conditions, disability, interpersonal discord, childhood experiences, and shelter history taken from either self-reported data or administrative records were taken as predictors. The author showed that deploying such a model would have increased the accuracy of targeting of services.

Another study (Byrne, Montgomery, & Fargo, 2019) has predicted housing instability and homelessness of Veterans who responded to the U.S. Department of Veterans Affairs' (VA) Homelessness Screening Clinical Reminder (HSCR). Self-reported housing instability status collected by the HSCR was predicted using prior medical history recorded in the VA's Corporate Data Warehouse, records of homeless program interactions taken from the VA's National Homeless Registry, and demographic variables including variables related to their military service. Findings demonstrated the ability to use electronic medical records in identifying veterans in the highest risk, for proactive and tailored interventions.

The Silicon Valley Triage Tool (Toros & Flaming, 2018) has identified homeless persons with high public services cost in Santa Clara County, California. These researchers used administrative data from 2007 to 2008 and predictors from the domains of criminal justice, health, HUD-funded homeless services, and public assistance provided by the County to flag if the homeless person will be in the top 10% of high-cost users in 2009. Unfortunately, the tool relied on integrating data from multiple systems, and few if any CoC systems would have access to the data required to deploy the method proposed in that paper.

Kube, Das, and Fowler (2019) predict the likelihood of reentry to homeless services within two years of initial contact. Unlike the papers reviewed above, the predictors and the target outcome were all sourced by the Homeless Management Information System (HMIS) of a major metropolitan area in the US. However, their interest is not in building a predictive risk model per se but to use these risk scores as a way of undertaking counter-factual analyses to determine the extent to which existing allocations of homelessness services are misallocated.

While the research efforts in building PRM tools suggests a widespread interest in data drive approaches to allocating homeless services, they are not deployable by most CoCs as they need to have real time ongoing access to integrated administrative data.

The goal of the present paper is to explore whether a machine learning algorithm-based predictive risk model using only standardized demographic data, data from the homeless system (i.e., HMIS), and self-reported answers to selected questions in the VI-SPDAT survey as predictors could improve upon the existing method of triaging. We confirm that all CoCs that have an HMIS – and have the ability to ask a sub-set of the VI-SPDAT questions – can use the proposed approach, to develop and deploy a data driven approach to homeless service coordination that is likely to be superior to existing tools in flagging clients at the greatest risk of adversities.

## Method

### Sample

The study sample is drawn from a medium size county in East Coast. We extract data from the Homeless Services Assessment and Coordination unit, for the period of January 2016–March 2017. The data set comprises 5,550 records, each record being an assessment for a client representing 4,364 unique clients in all.

Table 1 provides some summary statistics of the data. The percentage of females is 50%; the average age is 39 years; 50% are reported as Black or African American; 83% report that they have a disability; 31% of clients are assessed as a family (i.e., they are in a multi-person household), 62% identify as single and the rest identify as youth (defined as 18–24 years of age); 8% identified themselves as military veterans. 13% self-reported experiencing domestic violence as a contributing factor to their homelessness.

The County runs an integrated data warehouse which allowed us to link the 5,550 assessment records with County Jail and Medicaid data that could be used to generate outcomes with which to train the PRM. This linkage allows us to identify whether the clients had exposure to a set of adversities associated with homelessness within 12 months of housing assessments. We used four distinct outcomes to train the model. Table 2 provides a brief description of those outcomes and their associated prevalence.

### Feature engineering and selection

Housing service coordinators currently begin each homelessness assessment by asking a set of screening questions, to determine the interviewee's eligibility for the service and to select one of three VI-SPDAT survey types: Family, Youth, or Single. Including sub-questions, there are 49, 40,

**Table 1.** Characteristics of Assessed Clients.

| Characteristics | All clients [$n=4,364$] |
|---|---|
| Females (%) | 49.6 |
| Age- Mean (standard deviation) | 38.8 (13.7) |
| Black or African American (%) | 49.5 |
| Disability (%) | 83.3 |
| Household type: Family (%) | 30.9 |
| Household type: Single (%) | 61.9 |
| Household type: Youth (%) | 7.2 |
| Veteran status (%) | 7.5 |
| Reported experiencing Domestic Violence (DV) (%) | 13.0 |

*Notes:* Gender and Age data are from the basic information collected from VI-SPDAT surveys. Race data are obtained from the County's data warehouse. The race was not used as a predictor. Disability is counted when the response to the VI-SPDAT survey question "*Are you living with a disability?/Is anyone in the household living with a disability?,*" is '*yes*'. Family, Single, and Youth are defined based on the VI-SPDAT survey type. Veterans status is defined by the answer '*yes*' to the question: "*Have you served in the military?/Has anyone in your household served in the military?*". DV is defined as answering '*yes*' to the question: "*Are you currently experiencing domestic violence?/Is your family currently experiencing domestic violence?*". When there are multiple assessments for a person, only data from his/her most recent assessment is included.

**Table 2.** Description and Prevalence of Adversities used as Training Outcomes.

| Model training outcome | Description | Prevalence [$n=5,550$] |
|---|---|---|
| Mental Health Inpatient (MH Inpatient) | At least one Inpatient Mental Health service funded by Medicaid in the 12 months following the assessment | 16.0% |
| More than four Emergency Room visits (ER Visits >4) | More than four Emergency Room visits funded by Medicaid in the 12 months following the assessment | 20.5% |
| Night in Jail (Jail Night) | At least one County Jail booking in the 12 months following the assessment | 16.2% |
| Sustained Homelessness | Interactions with emergency shelter or street outreach in four distinct months in the 12 months following the assessment | 10.5% |

*Note:* The focus client in every record of our study sample was followed for 12 months from the date of assessment to recognize any interactions with Medicaid funded Behavioral and Physical Health, Jail, and HMIS using the unique client ID generated by County's data linkage system.

and 34 questions in Family, Youth, and Single VI-SPDAT surveys, respectively. In addition, the County gathers answers for two pre-survey questions and 31 additional questions that are not part of the VI-SPDAT surveys released in 2015 (OrgCode Consulting Inc. & Community Solutions, 2015a, 2015b, 2015c).

In total, there are 92 distinct questions that were asked from the clients. Table A1 (Appendix A) presents these questions by each survey type. For the purposes for our study, we extracted the answers to these 92 questions for each of the 5,550 records and converted them into categorical and or numerical predictors.

In addition to these questions, we also built predictors from the HMIS client management systems, extracting features of the client's previous contact with homeless services, as well as demographic information.

In summary, this process of feature engineering gave us a total of 608 predictors which consisted of 375 predictors coded from VI-SPDAT responses, 222 homeless service interactions predictors from the HMIS system, and 11 demographic predictors built from the demographic questions collected at the beginning of any housing assessment. Among the 222 housing service interactions predictors, 74 contained data corresponding to the homeless individual who is under assessment (focus client), and the remaining 148 are household-level predictors that represent data regarding children and other adults in that family. Table A2 (Appendix A) provides a brief description of predictors and some examples from each domain: VI-SPDAT survey responses, previous interactions with HUD funded housing services, previous interactions with County assisted housing services, demographics, and household make-up.

Due to the large number of survey questions that were needed to administer, we used a feature selection algorithm. The main objective of this task was to remove VI-SPDAT survey questions that are redundant in the presence of HMIS and demographic features. The initial set of 608 predictors with the aforementioned composition were assessed for their contribution to the outcome "presence of at least one of the training outcomes" given in Table 2. To that end, we utilized the correlation-based feature selection algorithm "CfsSubsetEval" (Hall, 1999) implemented in the WEKA (Frank, Hall, & Witten, 2016; Hall et al., 2009) machine learning workbench.[2] Taking 608 features as the input feature set, the "CfsSubsetEval" method finds the best subset of features that are highly correlated with the outcome while having low intercorrelation between them. Starting from the empty set, the search method "BestFirst" (Frank et al., 2016) explores the complete feature space in forward direction to find the features that are highly correlated with the outcome but are not correlated with the already selected features. The resulting feature subset included 84 VI-SPDAT predictors which were originated from only 15 out of the initial 92 survey questions. Those 15 questions are indicated in the last column of Table A1 (Appendix A). In addition to VI-SPDAT features, the best subset also included several HMIS interaction features and a demographic feature. However, at this stage, we do not drop any HMIS or demographic related predictors. Consequently, 317 features that comprise 84 VI-SPDAT responses related predictors (compared to the initial 375), 222 HMIS interaction related predictors, and 11 demographic predictors were used in the subsequent stage of model building.

## Model building

Having those 317 predictors and 4 individual target training outcomes, we formulated the PRM task as a supervised classification learning problem. Our prediction task is to build four separate predictive risk models for each of the outcomes of interest as defined in Table 2. Firstly, the study sample was partitioned into a training set containing 3,803 (69%) records and a testing set holding 1,747 (31%) records. When a record represents a client belonging to a family with more than one adult, all those family members were forced to be on either the training or testing set. This guarantees that the test data set is independent of the training data set even when family members hold similar household features. Additionally, the train partition was censored by assigning individuals who died in the 12 months following the assessment to the test partition.

We used Least Absolute Shrinkage and Selection Operator (LASSO) regularized logistic regression (Tibshirani, 1996) as the machine learning algorithm. The LASSO regularized Logistic Regression ensures certain predictor weights to be set to zero while minimizing prediction errors, given the sum of the absolute value of the weights is less than a constant that is often symbolized by lambda (λ). Thus, there is another stage of feature selection that is embedded into the learning algorithm. We built four PRMs, one for each of the four outcomes through the R package "glmnet" (Friedman, Hastie, & Tibshirani, 2010) version 3.0.[3] We tuned the model parameter λ through a 10-fold cross-validation procedure during the model training phase. There we trained a model on 9 folds and tested its performance on the remaining fold to select the optimum lambda in a way that minimizes bias. This method of applying K-fold cross-validation on the training set is suggested as an unbiased and appropriate (Friedman et al., 2010) alternative to setting a distinct validation set for parameter tuning, especially when the study sample size is limited. The λ that provides the best model performance which we measured in terms of the Area Under the Receiver Operating Characteristics (AUC) was taken as the optimum parameter value. The LASSO logistic regression model corresponding to the optimum λ value was chosen as the final model. Then, the final model was applied to the entire dataset to obtain predictions. Please note that the LASSO logistic regression implementation in the R package "glmnet" can produce either the class label (presence or absence of the harm) or the probability of a class as the result of a prediction task. We predict the latter so that we can rank one's risk likelihood. With the aim of recognizing risk scores that rank the level of vulnerability, predicted risk probabilities were categorized into 10 risk scores each of which were defined by a decile. For instance, the top 10% of probabilities were scored as 10 whereas the bottom 10% got 1 as the score. Predictive accuracy was evaluated using AUC, Positive Predictive Value (PPV), and the True Positive Rate (TPR) of each PRM score.

**Table 3.** Area Under the ROC Curve (AUC) for PRMs and VI-SPDAT Score.

| Adverse outcome | AUC and 95% c.i. of Each PRM- for Test Set only [$n = 1,747$] | AUC and 95% c.i. of VI-SPDAT [$n = 5,550$] |
|---|---|---|
| MH Inpatient | 75.7% [72.9%–78.5%] | 58.9% [57.0%–60.9%] |
| ER Visits >4 | 73.2% [70.3%–76.1%] | 56.7% [54.9%–58.5%] |
| Jail Night | 74.4% [71.3%–77.5%] | 56.6% [54.6%–58.6%] |
| Sustained Homelessness | 73.8% [69.7%–77.9%] | 55.6% [53.2%–58.1%] |

We next compared the accuracy of the PRM score against the VI-SPDAT tool that the County had been using to test whether they would benefit from the PRM tool. It is difficult to do a head-to-head comparison because the PRM tool is calibrated to have roughly 10% of the assessments in each of the one to ten scores, whereas with the VI-SPDAT, the scores range up to 22. We therefore grouped the VI-SPDAT so there was around 10% in each of the score "buckets." Note that the VI-SPDAT scores we use throughout this comparative study are wholly based on the questions and associated scores given in the VI-SPDAT surveys (OrgCode Consulting Inc. & Community Solutions, 2015a, 2015b, 2015c). Although the County gathered answers for additional questions, none of those responses were factored into the VI-SPDAT score we use in this study.

## Results

Table 3 presents AUCs and the 95% confidence intervals (c.i.) of each of the four PRM models that were trained on the four adverse outcomes. The AUC measure shows the ability of a given model to differentiate between the high and low likelihood of experiencing the particular harm that the model is trained to predict. Therefore, the AUC can be considered as the generalized predictive accuracy of a PRM that intends to classify risk. All measures tabulated for the PRMs are measured only on the test sample, hence we avoid reporting "over-fitted" statistics.

Among four classification models, the PRM trained on the MH Inpatient outcome reports the highest AUC: 75.7% (95% c.i. 72.9% to 78.5%). This means that a person with a MH Inpatient event in the next year has a 75.7% chance of receiving a larger risk score compared with a person who does not have an MH Inpatient event. On the other hand, the AUC of VI-SPDAT is 58.9% (95% c.i. 57.0%–60.9%) which means that it is almost random as to whether a person with an MH Inpatient event receives a higher VI-SPDAT score than a person without an MH Inpatient event.

Figures 1 and 2 illustrate the percentage of observed harm events among those who received a particular PRM risk score, and a VI-SPDAT score, respectively. This is the Positive Predictive Value (PPV) or in other words the precision of a risk score.

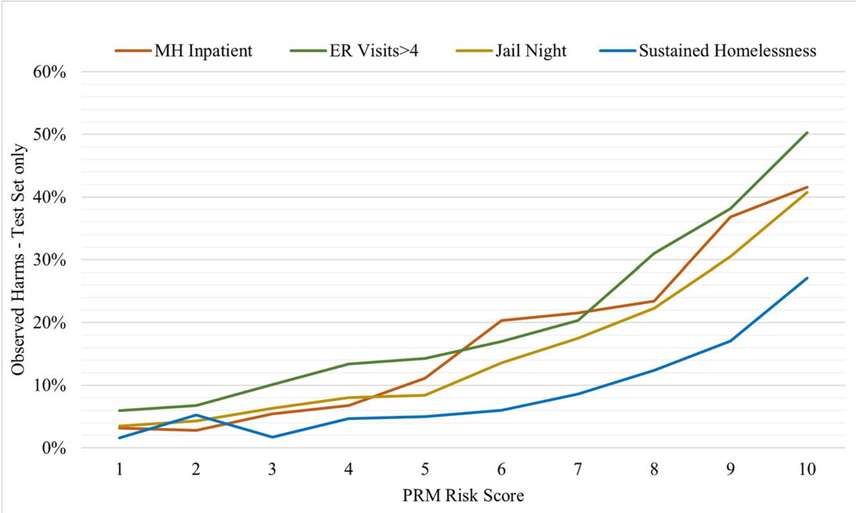


**Figure 1.** Prevalence of Adverse Outcomes by PRM Score (Test Set only).

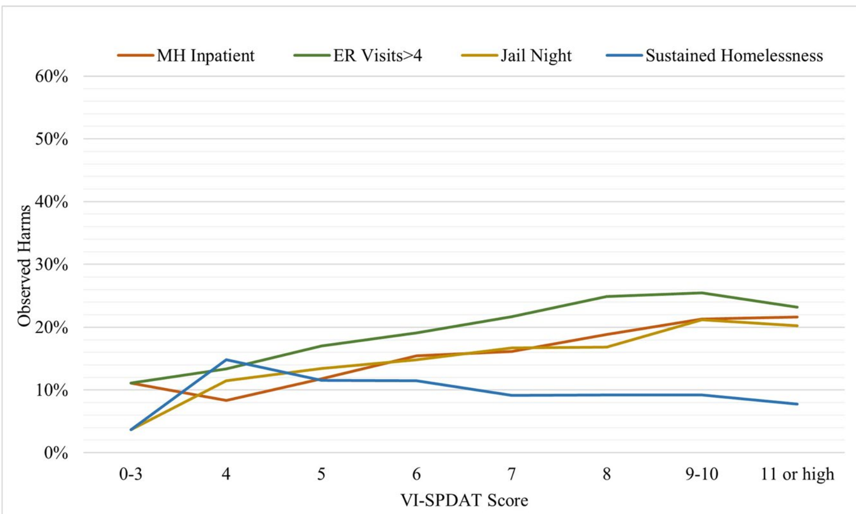


**Figure 2.** Prevalence of Adverse Outcomes by VI-SPDAT Score.

Almost half (50.26%) of assessments where the clients received a score of 10 ended up with more than 4 ER visits, in contrast, only 23.24% of assessed clients would have received a VI-SPDAT score in the top decile (11 or higher) implying that the PRM tool identifies people who are twice as likely to become a high user of ER compared with a person who score 11 plus in the VI-SPDAT tool. A similar positive gradient between the scores and the proportion of individuals who have the outcome is observed

**Table 4.** True Positive Rates (TPRs) of PRMs and VI-SPDAT score.

| | Proportion of records with adverse outcomes that are flagged in Top 10% by: | |
|---|---|---|
| Adverse outcome | Each PRM -for Test Set only | VI-SPDAT |
| MH Inpatient | 26.1% [21.1%, 31.0%] | 13.9% [11.6%, 16.1%] |
| ER Visits >4 | 26.5% [22.0%, 31.1%] | 11.6% [09.7%, 13.5%] |
| Jail Night | 27.8% [22.5%, 33.1%] | 12.8% [10.6%, 15.0%] |
| Sustained Homelessness | 30.8% [23.6%, 38.0%] | 07.6% [05.4%, 09.7%] |

for MH, a night in jail and sustained homelessness. Additionally, Figure 1 illustrates sensitivity of the adversities across the whole range of the PRM score, whereas for the VI-SPDAT score, the association between outcomes and score is weaker.

The use of Predictive Risk Modeling for triaging is essentially a ranking exercise. The aim is not to provide housing for every person who will be classified as having ER admission or a mental health crisis. Rather, the policy problem is to house those people who are at the highest risk. In the context of the County whose data we use, they are able to provide PSH only for around 10–15% of those people who are assessed. For this reason, we used the 10% cutoff as a policy relevant group of clients. The proportions of records with adverse outcomes that are flagged as the top 10% of risk by the PRM tool and the VI-SPDAT tool (the True Positive Rates or TPR) are compared in Table 4.

Accordingly, 26.1% of MH Inpatient events are flagged as high risk by the MH Inpatient PRM, whereas only 13.9% of those events are flagged by the VI-SPDAT. That is, the PRM flags almost four times as many people who end up with MH Inpatient stays as the VI-SPDAT tool. For the other events, including sustained homelessness, the PRM tool flags around one-third of true positives.

The next step is how to conceptualize whether the "right" group is at the elevated levels of risk that we would expect. We use relative risk of mortality as a way to do this. We validated the proposed PRM's assessment against having a recorded death within 12 months of assessment. The correlation between the risk score and mortality provides an additional validation of the approach. The overall death rate in the 12 months following an assessment was 1.5%. Table 5 presents each risk scoring method's sensitivity to mortality in terms of TPRs and relative risk. Those flagged as at risk by the PRM tools that were trained up MH inpatient and chronic ER use were at significantly elevated risk of death. In particular, those identified by the MH model were 3.2 times (95% c.i. of 2.0 to 5.2) as likely to die; and those identified by the chronic ER model were 2.7 times (95% c.i. of 1.6 to 4.4) as likely to die. The Jail model showed elevated mortality risk of 1.7, but this was not statistically significantly higher than 1 with 95% c.i.

**Table 5.** Sensitivity to Mortality.

| Assessment method | Assessment Score | Proportion of deaths within 12 months flagged [95% c.i.] | Relative risk of mortality [95% c.i.] |
|---|---|---|---|
| PRM model trained on MH Inpatient | 10 | 26.5% [17.0%, 36.0%] | 3.2 [2.0, 5.2] |
| PRM model trained on more than 4 ER Visits | 10 | 22.9% [13.8 %, 31.9%] | 2.7 [1.6, 4.4] |
| PRM model trained on more a Jail Night | 10 | 15.7% [07.8%, 23.5%] | 1.7 [0.9, 3.0] |
| PRM model trained on Sustained Homelessness | 10 | 09.6% [03.3 %, 16.0%] | 1.0 [0.5, 2.0] |
| VI-SPDAT | 11 plus | 10.8% [04.2%, 17.5%] | 1.1 [0.5, 2.1] |

between 0.9 and 3.0. Those at heightened risk of sustained homelessness were not at heightened risk of death. The VI-SPDAT tool showed no correlation with mortality (relative risk of 1.1 and 95% CI between 0.5 and 2.1).

## Discussion

### *Strengths*

The PRM models accurately predict those adversities that are associated with homelessness as well as sustained homelessness.

While the mortality rate of the population is too low to be a training outcome for a PRM model, our finding that individuals flagged as at highest risk of MH inpatient and chronic ER utilization are also at heightened risk of mortality suggests that these trained harms are correlated with more "ground truth" measures of future harm.

The PRM tool only requires answers to 15 questions (see Table A1 in Appendix A) i.e., far fewer than the questions required by the VI-SPDAT and the County. Given that many of these questions are intrusive and potentially stigmatizing, and difficult for persons in a crisis to answer, reducing the number of such questions is desirable; as well as leading to a considerable saving in time.

The proposed PRM does not just rely on client questions, but also on data gathered about the client in previous interactions using the HMIS data systems. This improves reliability, because rather than asking a client a question about their past homelessness, such as: "In the last three years, how many times have you been homeless?," we use previous contacts with the HMIS system as a more reliable proxy. This might account for the increased accuracy of the PRM tool over the traditional VI-SPDAT tool.

To implement a PRM solution as a prioritization decision aid, a local or state government only needs to rely on their standardized data collections. All the predictors we build are available to any CoC that has been using an electronic HMIS for around 3 years and is using the VI-SPDAT.

A one-off research exercise is required to identify clients' interactions with mental health, physical health, and jail systems using linked unidentified data to train the PRMs. Alternatively, after validating this approach in several jurisdictions, a more generalizable and similarly brief triage tool can be developed based on commonly valid items from the HMIS and the VI-SPDAT, especially for communities without access to linked administrative data.

### *Limitations*

Given that any prioritization tool affects which client receives a service, a limitation is a lack of true experimental data. The research data we use has some people receiving long term housing – and this is based on their VI-SPDAT score. If long term housing is protective, we might expect there to be an artificial reduction in the observed predictive accuracy because those with high scores are receiving protective services. We have conducted (unreported) experiments by excluding those who received services from the test set, and we found a very similar lack of correlation between the VI-SPDAT score and the harms.

Another limitation of this work is that the PRM was only trained on harms that are observed in administrative data. This restricted use to domains in mental health, physical health, jail nights, and sustained homelessness. Significantly, harms such as victimization of sexual violence or intimate partner violence are missing. Hence, it will be necessary to use this tool with some additional business rules that prioritize such victims when allocating resources.

A puzzling result is the lack of sensitivity to mortality that is observed with respect to people flagged as at risk of sustained homelessness, given the evidence that there are 3–4 times higher mortality rates among people experiencing homelessness; and that unsheltered adults have particularly high rates compared to the general homeless population (O'Connell, 2005; Roncarati et al., 2018). One reason could be that the outcome is conditional on surviving long enough to be seen in shelter and street outreach over a sustained period of time – and the survival bias might mean that we are unable to predict people who might have died as a result of being unsheltered.

Service use data will be missing for people who may not be users of services, yet in need of them. For people whose service utilization history occurred in a different geographic area than where the homelessness assessment is being done (a different state or county), predictive data will also be missing. These coverage gaps limit may mean that people will not be properly classified for their risk.

## Further research

Even if the proposed PRM tool reduces the number of questions in total to be asked of a client, some stigmatizing and invasive questions are still retained. For example, the PRM requires the following question to be answered: "In the past six months, how many times have you used a crisis service, including sexual assault crisis, mental health crisis, family/intimate violence, distress centers and suicide prevention hotlines?." Further research into which questions clients are least comfortable with, and where responses are most unreliable, and replacing them with questions that are as predictive, but less stigmatizing would be desirable. An important question that we have not looked at is whether these methods of prioritization are biased in the way they treat people of different racial groups or gender.

## Conclusion

This paper has illustrated the superior predictive accuracy of machine learning tools for prioritization of homeless services, and that these tools can be built using existing single data systems. Agencies and jurisdictions do not have to wait for integrated data to start exploiting PRM methods. The PRM based decision aid proposed in this research combines a short list of questions with data from the homelessness administrative systems. Our findings suggest that PRM can allow an agency to find clients at considerably heightened risk of harm compared to existing approaches.

## Notes

1. This article refers to the VI-SPDAT surveys launched in 2015 due to its correspondence with the study data sample and the duration.
2. https://www.cs.waikato.ac.nz/ml/weka/
3. https://cran.r-project.org/src/contrib/Archive/glmnet/

## Disclosure statement

Authors Rhema Vaithianathan and Chamari I. Kithulgoda report grants for their involvement in the project, developing predictive risk model to prioritize services for people experiencing homelessness in Allegheny County, PA, where they have taken research data for the present article.

## Data availability statement

Restrictions apply to the availability of these data. Access to these data may be arranged on a case-by-case basis upon application to Allegheny County Department of Human Services.

## Ethics declaration

This research was reviewed and approved by the Auckland University of Technology Ethics Committee, reference number 20/176. The requirement for informed consent was waived by the committee.

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## Appendix A

**Table A1.** List of distinct VI-SPDAT Survey Questions for Families, Single, and Transition Age Youth as of existing tool and proposed PRM tool.

| Index | Question | Required for Family VI-SPDAT | Required for Single VI-SPDAT | Required for Youth VI-SPDAT | Required for PRM |
|---|---|---|---|---|---|
| 1 | What is your current housing crisis? | Pre-survey questions | | | |
| 2 | If facing eviction, how many months behind in rent? | | | | |
| 3 | Is this individual 60 years of age or older? | Yes | Yes | No | No |
| 4 | Where do you sleep most frequently? /Where do you and your family sleep most frequently? | Yes | Yes | Yes | No |
| 5 | How long has it been since you have lived in permanent stable housing? / How long has it been since you and your family have lived in permanent stable housing? | Yes | Yes | Yes | No |
| 6 | In the last three years, how many times have you been homeless? /In the last three years, how many times have you and your family been homeless? | Yes | Yes | Yes | No |
| 7 | Is this individual/household chronically homeless? | Additional question | | | No |
| 8 | Have you served in the military? /Has anyone in your household served in the military? | Additional question | | | No |
| 9 | Are you living with a disability? /Is anyone in the household living with a disability? | Additional question | | | No |
| 10 | **In the past six months, how many times have you received health care at an emergency department/room?** | Yes | Yes | Yes | **Yes** |
| 11 | **In the past six months, how many times have you taken an ambulance to the hospital?** | Yes | Yes | Yes | **Yes** |
| 12 | **In the past six months, how many times have you been hospitalized as an inpatient?** | Yes | Yes | Yes | **Yes** |
| 13 | **In the past six months, how many times have you used a crisis service, including sexual assault crisis, mental health crisis, family/intimate violence, distress centers and suicide prevention hotlines?** | Yes | Yes | Yes | **Yes** |
| 14 | In the past six months, how many times have you talked to police because you witnessed a crime, were the victim of a crime, or the alleged perpetrator of a crime or because the police told you that you must move along? | Yes | Yes | Yes | No |
| 15 | **In the past six months, how many times have you stayed one night in a holding cell, jail, or prison, whether that was a short-term stay like a drunk tank, a longer stay for a more serious offense, or anything in between?** | Yes | Yes | Yes | **Yes** |
| 16 | Have you been attacked or beaten up since you have become homeless? /Have you or anyone in your family been attacked or beaten up since they have become homeless? | Yes | Yes | Yes | No |
| 17 | Have you threatened to or tried to harm yourself or anyone else in the last year? /Have you or anyone in your family threatened to or tried to harm themself or anyone else in the last year? | Yes | Yes | Yes | No |
| 18 | **Does anyone have a criminal history?** | Additional question | | | **Yes** |
| 19 | Megan's Law Registrant? | Additional question | | | No |
| 20 | Arson Conviction? | Additional question | | | No |

(*Continued*)

**Table A1.** (Continued).

| Index | Question | Required for Family VI-SPDAT | Required for Single VI-SPDAT | Required for Youth VI-SPDAT | Required for PRM |
|---|---|---|---|---|---|
| 21 | Do you have any legal stuff going on right now that may result in you being locked up, having to pay fines, or that make it more difficult to rent a place to live?/Does anyone in your family have any legal stuff going on right now that may result in you being locked up, having to pay fines, or that make it more difficult to rent a place to live? | Yes | Yes | Yes | No |
| 22 | Does anybody force or trick you to do things that you do not want to do? /Does anybody force or trick anyone in your family to do things that you do not want to do? | Yes | Yes | Yes | No |
| 23 | **Do you ever do things that may be considered to be risky like exchange sex for money, run drugs for someone, have unprotected sex with someone you don't know, share a needle, or anything like that? / Do you or anyone in your family ever do things that may be considered to be risky like exchange sex for money, run drugs for someone, have unprotected sex with someone you don't know, share a needle, or anything like that?** | Yes | Yes | Yes | **Yes** |
| 24 | Is there any person, past landlord, business, bookie, dealer, or government group like the IRS that thinks you owe them money? /Is there any person, past landlord, business, bookie, dealer, or government group like the IRS that thinks you or anyone in your family owe them money? | Yes | Yes | Yes | No |
| 25 | Do you get any money from the government, a pension, an inheritance, working under the table, a regular job, or anything like that? /Do you or anyone in your family get any money from the government, a pension, an inheritance, working under the table, a regular job, or anything like that? | Yes | Yes | Yes | No |
| 26 | **What is the total household income?** | Additional question | | | **Yes** |
| 27 | **Percentage of Area Median Income (AMI)** | Additional question | | | **Yes** |
| 28 | Percentage of Federal Poverty Level (FPL) | Additional question | | | No |
| 29 | Do you have any planned activities, other than just surviving, that make you feel happy and fulfilled? /Does everyone in your family have any planned activities, other than just surviving, that make you feel happy and fulfilled? | Yes | Yes | Yes | No |
| 30 | Are you currently able to take care of basic needs like bathing, changing clothes, using a restroom, getting food and clean water and other things like that? /Is everyone in your family currently able to take care of basic needs like bathing, changing clothes, using a restroom, getting food and clean water and other things like that? | Yes | Yes | Yes | No |
| 31 | Is your current homelessness in any way caused by a relationship that broke down, an unhealthy or abusive relationship, or because family or friends caused you to become evicted? /Is your family's current homelessness in any way caused by a relationship that broke down, an unhealthy or abusive relationship, or because family or friends caused you to become evicted? | Yes | Yes | No | No |

| | | | | | |
|---|---|---|---|---|---|
| 32 | Are you currently experiencing domestic violence? /Is your family currently experiencing domestic violence? | Additional question | | | No |
| 33 | Have you ever had to leave an apartment, shelter program, or other place you were staying because of your physical health? /Has your family ever had to leave an apartment, shelter program, or other place you were | Yes | Yes | Yes | No |
| 34 | Does the head of the household have a chronic health condition? | Additional question | | | No |
| 35 | Do you have any chronic health issues with your liver, kidneys, stomach, lungs, or heart? /Do you or anyone in your family have any chronic health issues with your liver, kidneys, stomach, lungs, or heart? | Yes | Yes | Yes | No |
| 36 | Are you living with HIV/AIDS? /Is anyone in the household living with HIV/AIDS? | Additional question | | | No |
| 37 | If there was a space available in a program that specifically assists people that live with HIV or AIDS, would that be of interest to you? /If there was a space available in a program that specifically assists people that live with HIV or AIDS, would that be of interest to you or anyone in your family? | Yes | Yes | Yes | No |
| 38 | Do you have any physical disabilities that would limit the type of housing you could access, or would make it hard to live independently because you would need help? /Does anyone in your family have any physical disabilities that would limit the type of housing you could access, or would make it hard to live independently because you would need help? | Yes | Yes | Yes | No |
| 39 | Do you need a wheelchair accessible unit? | Additional question | | | No |
| 40 | Requires a wheelchair accessible unit exclusively? | Additional question | | | No |
| 41 | When you are sick or not feeling well, do you avoid getting help? /When someone in your family is sick or not feeling well, does your family avoid getting medical help? | Yes | Yes | Yes | No |
| 42 | For Female Respondents Only: Are you currently pregnant? /If household includes a female: Is any member of the family currently pregnant? | Yes | Yes | Yes | No |
| 43 | How far along in your pregnancy are you? | Additional question | | | No |
| 44 | Do you use drugs or alcohol? /Do you or anyone in your household use drugs or alcohol? | Additional question | | | No |
| 45 | **When was the last time you used drugs or alcohol? /When was the last time they used drugs or alcohol?** | Additional question | | | **Yes** |
| 46 | Are you willing to not use drugs and alcohol to be eligible for a housing program? | Additional question | | | No |
| 47 | Has your drinking or drug use led you to being kicked out of an apartment or program where you were staying in the past? /Has your drinking or drug use by you or anyone in your family led you to being kicked out of an apartment or program where you were staying in the past? | Yes | Yes | Yes | No |
| 48 | Will drinking or drug use make it difficult for you to stay housed or afford your housing? /Will drinking or drug use make it difficult for your family to stay housed or afford your housing? | Yes | Yes | Yes | No |

(*Continued*)

**Table A1.** (Continued).

| Index | Question | Required for Family VI-SPDAT | Required for Single VI-SPDAT | Required for Youth VI-SPDAT | Required for PRM |
|---|---|---|---|---|---|
| 49 | Have you ever had trouble maintaining your housing, or been kicked out of an apartment, shelter program or other place you were staying, because of: A mental health issue or concern? | Yes | Yes | Yes | No |
| 50 | Have you ever had trouble maintaining your housing, or been kicked out of an apartment, shelter program or other place you were staying, because of: A past head injury? | Yes | Yes | Yes | No |
| 51 | Have you ever had trouble maintaining your housing, or been kicked out of an apartment, shelter program or other place you were staying, because of: A learning disability, developmental disability, or other impairment? | Yes | Yes | Yes | No |
| 52 | Do you have any mental health or brain issues that would make it hard for you to live independently because you would need help? /Do you or anyone in your family have any mental health or brain issues that would make it hard for you to live independently because help would be needed? | Yes | Yes | Yes | No |
| 53 | Are there any medications that a doctor said you should be taking that, for whatever reason, you are not taking? /Are there any medications that a doctor said you or anyone in your family should be taking that, for whatever reason, they are not taking? | Yes | Yes | Yes | No |
| 54 | Are there any medications like painkillers that you do not take the way the doctor prescribed or where you sell the medication? /Are there any medications like painkillers that you or anyone in your family do not take the way the doctor prescribed or where you sell the medication? | Yes | Yes | Yes | No |
| 55 | Has your current period of homelessness been caused by an experience of emotional, physical, psychological, sexual, or other type of abuse, or by any other trauma you have experienced? / Has your family's current period of homelessness been caused by an experience of emotional, physical, psychological, sexual, or other type of abuse, or by any other trauma you or anyone in your family have experienced? | Yes | Yes | No | No |
| 56 | How many children under the age of 18 are currently with you? | Yes | No | No | No |
| 57 | How many children under the age of 18 are not currently with your family, but you have reason to believe they will be joining you when you get housed? | Yes | No | No | No |
| 58 | **Has anyone ever told you that you have a mental health diagnosis such as depression, bipolar, Schizophrenia or anything like that? /Has anyone ever told you that you or anyone in your family have a mental health diagnosis such as depression, bipolar, Schizophrenia or anything like that?** | Additional question | | | **Yes** |
| 59 | If the family scored 1 for each for physical health, substance use, and mental health:<br>Does any single member of your household have a medical condition, mental health concern, and experience problematic substance use? | Yes | No | No | No |
| 60 | Were you involved in the child welfare system when turning 18? /Was anyone in your household involved in the child welfare system when turning 18? | Additional question | | | No |

| | | | | | |
|---|---|---|---|---|---|
| 61 | **Are there any children that have been removed from the family by a child protection service within the last 180 days?** | Yes | No | No | **Yes** |
| 62 | Do you have any family legal issues that are being resolved in court or need to be resolved in court that would impact your housing or who may live within your housing? | Yes | No | No | No |
| 63 | In the last 180 days have any children lived with family or friends because of your homelessness or housing situation? | Yes | No | No | No |
| 64 | Has any child in the family experienced abuse or trauma in the last 180 days? | Yes | No | No | No |
| 65 | IF THERE ARE SCHOOL-AGED CHILDREN: Do your children attend school more often than not each week? | Yes | No | No | No |
| 66 | Have the members of your family changed in the last 180 days, due to things like divorce, your kids coming back to live with you, someone leaving for military service or incarceration, a relative moving in, or anything like that? | Yes | No | No | No |
| 67 | Do you anticipate any other adults or children coming to live with you within the first 180 days of being housed? | Yes | No | No | No |
| 68 | Do you have two or more planned activities each week as a family such as outings to the park, going to the library, visiting other family, watching a family movie, or anything like that? | Yes | No | No | No |
| 69 | 3 or more hours per day for children aged 13 or older? | Yes | No | No | No |
| 70 | 2 or more hours per day for children aged 12 or younger? | Yes | No | No | No |
| 71 | **If there are children both 12 and under 13 and over: Do your older kids spend 2 or more hours on a typical day helping their younger sibling(s) with things like getting ready for school, helping with homework, making them dinner, bathing them, or anything like that?** | Yes | No | No | **Yes** |
| 72 | **How many parents are in this household?** | Yes | No | No | **Yes** |
| 73 | Of those times you were homeless, how many times have you been street homeless? /Of those times you were homeless, how many times have you and your family been street homeless? | Additional question | | | No |
| 74 | If you had to put all those times together, how long it would be? | Additional question | | | No |
| 75 | **Is the Head of Household living with a disability?** | Additional question | | | **Yes** |
| 76 | How long have you been street homeless (Street, Shelter, Safe Haven)? /How long have you and your family been street homeless (Street, Shelter, Safe Haven)? | Additional question | | | No |
| 77 | If a housing provider asked you to take a drug test-would you pass? | Additional question | | | No |
| 78 | Is this individual 17 years of age or less? | No | No | Yes | No |
| 79 | Were you ever incarcerated when younger than 18? | No | No | Yes | No |
| 80 | Is your current lack of stable housing: Because you ran away from your family home, a group home, or a foster home? | No | No | Yes | No |

(*Continued*)

**Table A1.** (Continued).

| Index | Question | Required for Family VI-SPDAT | Required for Single VI-SPDAT | Required for Youth VI-SPDAT | Required for PRM |
|---|---|---|---|---|---|
| 81 | Is your current lack of stable housing: Because of a difference in religious or cultural beliefs from your parents, guardians, or caregivers? | No | No | Yes | No |
| 82 | Is your current lack of stable housing: Because your family or friends caused you to become homeless? | No | No | Yes | No |
| 83 | Is your current lack of stable housing: Because of conflicts around gender identity or sexual orientation? | No | No | Yes | No |
| 84 | Is your current lack of stable housing: Because of violence at home between family members? | No | No | Yes | No |
| 85 | Is your current lack of stable housing: Because of an unhealthy or abusive relationship, either at home or elsewhere? | No | No | Yes | No |
| 86 | If you have ever used marijuana, did you ever try it at 12 or younger? | No | No | Yes | No |
| 87 | Where did you sleep last night/where will you sleep tonight? | Additional question | | | No |
| 88 | Approximately what date did your current homeless episode begin? | Additional question | | | No |
| 89 | Are you currently working with any of the street outreach teams? | Additional question | | | No |
| 90 | If so, who you are working with? | Additional question | | | No |
| 91 | Where do you sleep when you are outside? | Additional question | | | No |
| 92 | Have you ever been diagnosed with, told, or feel that you have a substance use disorder? /Have you or anyone in your family ever been diagnosed with, told, or feel that they have a substance use disorder? | Additional question | | | No |

*Note:* Additional questions are adopted from the County's Homeless Services and Supports Coordination unit.

**Table A2.** Overview of Coded Features used in the PRM Tool.

| Domain | Description | Examples |
|---|---|---|
| VI-SPDAT survey responses | Answers collected through VI-SPDAT survey questions | Number of inpatient hospitalizations happened in the past six months, if their children have been removed by a child protection service within the last six months, count of parents in the household |
| Previous interactions with HUD funded housing services | Features related to interactions or to the duration spent in PSH, Transitional, Prevention service program, Shelter and Street Outreach at present, in the last year, last 2 years, last 3 years, or before. | Number of episodes spent in PSH program in the last year, whether the client is in a Shelter program at the time of the assessment |
| Previous interactions with County assisted housing services | Features related to the interactions or to the duration spent in public housing support from County's Housing Authority in the last year, last 2 years, last 3 years, or before. | Count of months spent in public housing support from the Housing Authority in the last year, Whether the client is in those housing facilities at the time of the assessment |
| Demographics | Age and gender information | Whether the focus client is a Female, Age of the focus client |
| Household | Family members' demographics, interactions with Homeless services and public housing support from the County | In case of a family assessment: number of adults in Prevention program at the time of the assessment, number of teenagers in the household |