



VA NATIONAL CENTER ON HOMELESSNESS AMONG VETERANS

*Research-driven solutions to prevent and end homelessness*

## HOMELESS EVIDENCE AND RESEARCH SYNTHESIS (HERS) ROUNDTABLE PROCEEDINGS

### **Potential Benefits and Pitfalls in Predictive Analytics Among Veterans Experiencing Homelessness**

July 31, 2019

## **Homeless Evidence and Research Synthesis (HERS) Roundtable Series**

The National Center on Homelessness among Veterans (the Center) in the Veterans Health Administration (VHA) established the Homeless Evidence and Research Synthesis (HERS) Roundtable Series in 2015 as a policy forum. The virtual symposium convenes researchers and subject matter experts to discuss research findings on key issues in homelessness. The online webinar is available to interested parties within and outside of the U.S. Department of Veterans Affairs (VA). Topics covered to date include: **Enumeration of Homelessness** (July, 2015); **Aging and the Homeless Community** (November, 2015); **Women Veterans and Homelessness** (May, 2016); **Opioid Use Disorder and Homelessness** (February, 2017); **Rural Veterans and Homelessness** (June, 2017); **Suicide and Homeless Veterans** (February, 2018); **Addressing Social Determinants of Health: Exploring Implications for Policy through the Veteran Health Administration’s Universal Screening for Housing Instability among Veteran Outpatients** (September, 2018); and **Potential Benefits and Pitfalls in Predictive Analytics Among Veterans Experiencing Homelessness**.

Links to the recorded webinars and proceedings are available on the Center website.

<https://www.va.gov/HOMELESS/nchav/research/HERS.asp>

## Potential Benefits and Pitfalls in Predictive Analytics Among Veterans Experiencing Homelessness

The proceedings of **Potential Benefits and Pitfalls in Predictive Analytics Among Veterans Experiencing Homelessness** are a summary of the presentations and roundtable discussion that took place on July 31, 2019 in a virtual symposium. The recorded webinar and downloadable copies of the individual presentations are available here <http://va-eerc-ees.adobeconnect.com/polj8vlnkbtq/>.

### Moderator

**Dina Hooshyar**, MD, MPH, Director, National Center on Homelessness among Veterans

### Presenters and Roundtable Panel

**Stephan Fihn**, MD, MPH, Professor of Medicine and Health Services, Division Head, General Internal Medicine, University of Washington

**Daniel Flaming**, PhD, President, Economic Roundtable

**Elizabeth Heitman**, PhD, Professor, Ethics in Science and Medicine, University of Texas Southwestern Medical Center

**James Marquez**, MBA, Senior Data Scientist, Veterans Health Administration

**Jodie Trafton**, PhD, Director, Program Evaluation and Resource Center, Office of Mental Health and Suicide Prevention, Veterans Health Administration; Clinical Professor (affiliated), Stanford University, Department of Psychiatry and Behavioral Sciences

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## Executive Summary

Predictive analytics – the use of health-related data to predict the likelihood of future events – has been expanding since the 1970’s and has been used in clinical care for many years, including within the US Department of Veterans Affairs (VA). The availability of massive data sets that include electronic clinical health records, modern database technology, and sophisticated software has led to an explosion of efforts to predict a wide range of events that include death, hospitalization, and variety of clinical complications. In this Homeless Evidence Research Synthesis (HERS) webinar, individuals with clinical, research and software design experience in predictive analytics provided a glimpse into the science and art of the field. They shared examples of predictive models currently being used in the Veterans Health Administration (VHA) to address risk for hospitalization, suicide, and overdose and discussed outcomes to date. A pilot program outside VA that is using predictive screening tools to prevent chronic homelessness in Los Angeles offered promise and demonstrated how the science might be applied to VHA’s work to address homelessness and risk among Veterans.

Predictive modeling -- paired with well-designed decision support tools -- has the potential to save time, money, and lives by alerting clinicians about individuals at risk of adverse health events and targeting them for preventive care. However, models are subject to imperfection, due to incomplete data, bias, or other “wrenches.” In addition, as Jodie Trafton observed, even the good models “are only as helpful as the clinical practices they’re embedded in.” Addressing this challenge, James Marquez offered suggestions for designing user-friendly web-based clinical applications, both to help clinicians better target and manage treatment for their patients and to aid oversight of care by administrative leadership.

Both Stephan Fihn and Dr. Trafton recommended that predictive models be tested in clinical trials. However, there was concern that models may be widely adopted without rigorous testing. Elizabeth Heitman highlighted ethical considerations around patients’ privacy and systems that may either leave them out of services or coerce them into programs they do not want. Daniel Flaming suggested that predictive screening can do much to prevent harm by *giving* something to people, rather than taking it away: “Predictive tools can be used to identify people for a variety of risks but they can also be used to identify possibilities for maximizing people’s potential – in our case – employment.” Perhaps Dr. Fihn summed up the discussion best in saying, “We all think we’re good at prediction, but in general we’re not very good at thinking in probabilistic terms... we’re subject to a large number of cognitive biases. Computers are going to a better job, but with all of the caveats that have been raised.”

## Presentations

### Predictive Analytics in Health Care

**Stephan Fihn, MD, MPH**

Predictive analytics – the use of health-related data to predict the likelihood of future events – has been expanding since the 1970’s and has been used in clinical care for many years, including within VA. The availability of massive data sets that include clinical (Electronic Health Record-EHR) data, modern database technology, and sophisticated software, including AI (Artificial Intelligence) has led to an explosion of efforts to predict a wide range of events that include death, hospitalization, and variety of clinical complications.

#### *Statistical and governance considerations*

Modern models have become highly accurate but there is no agreement among statisticians on the best way to measure accuracy. In addition, models developed on one dataset or in one health system typically do not perform as well on a different one. They require extensive validation with ongoing

maintenance and recalibration. Another issue is the possibility of detection bias in the model, based on limited data for certain patients. These tend to be the highest risk patients who may not receive all of the care they need and deserve. To the degree that their data may be missing, the model may not work well for them.

Beyond statistical considerations, there are also several governance issues to weigh when installing or implementing a predictive model in a health system. These include organizational capabilities, personnel capacity, cost, cybersecurity and privacy, ethics and fairness, safety and efficacy surveillance, and regulatory issues, as outlined in Figure 1.

**Figure 1: Governance Issues in Predictive Model Development**

Governance Issues in Predictive Model Development	
<b>Organizational capabilities</b>	Does the organization possess the necessary technologic (e.g., IT infrastructure, IT personnel) and organizational (knowledgeable and engaged workforce, educational and training) capabilities to adopt, assess and maintain AI driven tools?
<b>Data Environment</b>	What data are available for AI development? Do current systems possess adequate capacity for storage, retrieval and transmission to support AI tools?
<b>Interoperability</b>	Does the organization support and maintain data at rest and in motion that meet national and local standards for interoperability (e.g., SMART on FHIR)
<b>Personnel Capacity</b>	What expertise exists in the health care system to develop and maintain the AI algorithms?
<b>Cost, Revenue &amp; Value</b>	What will be the initial and ongoing costs to purchase, install, and train users to maintain underlying data models and to monitor for variance in model performance? Is there an anticipated ROI from the AI deployment? What is the perceived value for the institution related to AI deployment?
<b>Safety &amp; Efficacy Surveillance</b>	Are there governance and processes in place to provide regular assessments of the safety and efficacy for AI tools?
<b>Cybersecurity &amp; Privacy</b>	Does the digital infrastructure for health care data in the enterprise have sufficient protections in place to minimize the risk of breaches of privacy or data security if AI is deployed?
<b>Ethics &amp; Fairness</b>	Is there infrastructure in place to provide oversight and review of AI tools to ensure that the known issues around ethics and fairness are addressed and vigilance for unknown issues is in place?
<b>Regulatory issues</b>	Are there specific regulatory issues that must be addressed and, if so, what type of monitoring and compliance programs will be necessary?

### *Clinical Deployment*

The process of model deployment is iterative: it depends on understanding the clinical workflow and implementing the model in practice within the existing infrastructure; monitoring the ongoing performance of the AI application and tracking changes in culture and workflow; and updating, modifying, adapting or de-implementing, as warranted. Dr. Fihn cited the example of the Care Assessment Need (CAN) Score that he developed with a VA team in 2010 to estimate the probability of hospital admission or death within certain times frames for Veterans enrolled in primary care. Originally derived with data on more than 4 million Veterans, the model predicts high risk patients with great accuracy and the application has been available to clinicians since 2012. (1) However, a recent study of

CAN usage in 2016-2017 indicated that 15 to 20% of primary care providers were using it and that there was great variability in usage by VISN (VA Integrated Service Network), from virtually every provider using it in one VISN to practically none in another. (2) “The big issues are not model development but model implementation,” according to Dr. Fihn. “Of the thousands of papers that have been published on predictive models, only a handful of models have been integrated into clinical workflows and many have shown little or no clinical effects.” (3)

## **VA Suicide and Overdose Prevention: Leveraging Big Data**

### **Jodie Trafton, PhD**

Jodie Trafton shared findings regarding implementation from two predictive models that the Office of Mental Health and Suicide Prevention has been using to prevent suicide and overdose. Using VHA’s Corporate Data Warehouse (CDW) and Business Intelligence Service Line reporting solutions, the office has developed the REACH VET (Recovery Engagement and Coordination for Health – Veterans Enhanced Treatment) and STORM (Stratification Tool for Opioid Risk Mitigation) predictive models to identify VHA patients likely to have a negative outcome, such as die by suicide, or overdose. The models have been incorporated into clinical decision support dashboards which are used in programs that target outreach and prevention interventions to patients at highest risk at all 141 VHA Health Care Systems.

#### ***REACH VET 1.0 Initial Findings***

The REACH VET predictive model, which estimates risk of death by suicide in the next month, ranked risk for patients at all health system centers. Patients in the top 0.1% (over 31,000) were presented to care coordinators who alerted these patients’ clinicians. Their clinicians then engaged these patients in further care as needed. In its first year of operation, REACH VET improved outcomes for those targeted, as compared to matched patients prior to the implementation of the intervention or to patients just below the threshold for receiving the intervention. This improvement was measured by: significantly greater increases in health care appointments and outpatient mental health care; new clinically established suicide safety plans; fewer inpatient mental health admissions and emergency department visits; and lower all-cause mortality in the next 6 months of 1.9% versus 2.9% in a prior year control, which would equate to 310 lives.

#### ***STORM 1.0: Experience to Date***

STORM estimates risk of overdose or suicide events for all patients prescribed or considering an opioid analgesic. It combines risk estimates with patient-tailored recommendations of interventions, based on VA/Department of Defense Clinical Practice Guidelines, to reduce risk and improve pain management. The tool is available to all VHA clinicians and its reports have been accessed more than 470,000 times by over 14,000 clinicians. The STORM predictive model greatly improves on single risk factor-based approaches for targeting patients at risk of overdose or suicide. For example, targeting attention to the top 20,000 STORM model patients would identify 24% of all VA patients who will have an overdose or suicide event in the next year. Targeting attention to the top 20,000 patients on very high dose of opioids (i.e., over 200mg) would only identify 3.7% of VA patients who will have an overdose and suicide event. Patients estimated to be at very high risk receive a case review by an interdisciplinary team with pain, mental health, and addiction expertise to make sure they are getting the most appropriate care and have been provided the appropriate preventative safety intervention. If the patient’s care looks good, the person won’t know that their care was reviewed. If it looks like there are things the care team could do to make the care safer, the team will reach out to the patient to suggest augmentations or

improvements to care. In preliminary analyses, this has led to consistent clinical follow up of all patients and increased rates of overdose education and naloxone distribution.

### Clinical Implementation of Predictive Modeling

VHA has shown that predictive modeling can enrich information about target populations to enable proactive clinical attention to those at risk of suicide or overdose. This information can be shared with clinicians in everyday clinical practice via decision support platforms. In short, proactive clinical care based on big data is feasible and effective.

## Operationalizing Predictive Analytic Models for Use by Clinicians

James Marquez, MBA

Following on Dr. Trafton’s examples of effective decision support platforms, James Marquez discussed how to design decision support tools that clinicians will actually use. He shared lessons learned in building Intelligent Preventive Care (IPC), a custom web application that combines the ACSC Risk 3M, CAN, Reach VET and STORM models and is currently in use at 84 VA facilities.

### Supporting Clinicians

His tips include building a clean user interface with a minimal number of options available to the clinician and simplifying the searching and filtering needed to view actionable information: monitoring required actions on patients with predicted outcomes. A sample screen from the IPC application (Figure 2) shows, at a glance, a list of the clinician’s high risk patients based on the predictive models applied, their high risk conditions, and the recommended care.

Figure 2: Sample Screen from Intelligent Preventive Care Web Application

Veteran	High-Risk Models	Recommended Care	High Risk Conditions
<p><b>E0000</b>                      Example Patient                      000-00-0000                      AID &amp; ATTENDANCE                      73 yrs                      Cell: (555) 555-5555                      Res: (555) 555-5555                      Temp: (555) 555-5556</p>	<p>ACSC Risk3M Rank: 95                      CAN Hosp 90d: 90                      CAN Hosp 1y: 95                      Potentially Homeless</p>	<p><b>PCP Appt</b>  <b>Nutrition/MOVE Appt</b>  <b>Home Telehealth</b></p>	<p>Hypertension</p>
<p><b>E0000</b>                      Example Patient                      000-00-0000                      AID &amp; ATTENDANCE                      73 yrs                      Cell: (555) 555-5555                      Res: (555) 555-5555                      Temp: (555) 555-5555</p>	<p>ACSC Risk3M Rank: 95                      CAN Hosp 90d: 90                      CAN Hosp 1y: 85</p>	<p><b>PCP Appt</b>  <b>Cardiology Appt</b></p>	<p>Diabetes Long-Term Complications                      Diabetes Short-Term Complications                      Heart Failure                      Hypertension                      Urinary Tract Infection</p>
<p><b>E0000</b>                      Example Patient                      000-00-0000                      AID &amp; ATTENDANCE                      73 yrs                      Cell: (555) 555-5555                      Res: (555) 555-5555                      Temp: (555) 555-5565</p>	<p>ACSC Risk3M Rank: 99                      REACH VET: Highest                      CAN Mort 90d: 90                      CAN Mort 1y: 95                      CAN Hosp 90d: 99                      CAN Hosp 1y: 99                      Tobacco User Every Day                      Tobacco User Some Days</p>	<p><b>PCP Appt</b>  <b>Care Mgr Visit</b>  <b>Pulmonary Appt</b>  <b>Nutrition/MOVE Appt</b></p>	<p>Angina Without Procedure                      Chronic Obstructive Pulmonary Disease (COPD)                      Dehydration                      Diabetes Long-Term Complications                      Diabetes Short-Term Complications                      Heart Failure                      Uncontrolled Diabetes  <b>CHF Admission</b>  <b>Angina Admission</b>  <b>CHF Admission</b>  <b>Dehydration Admission</b></p>

### Informing Leadership

In addition to aiding clinicians, it is important to develop a scorecard for leadership that maps the preventive care actions recommended and the extent to which they have been completed, as shown in the sample scorecard report below. (Figure 3)

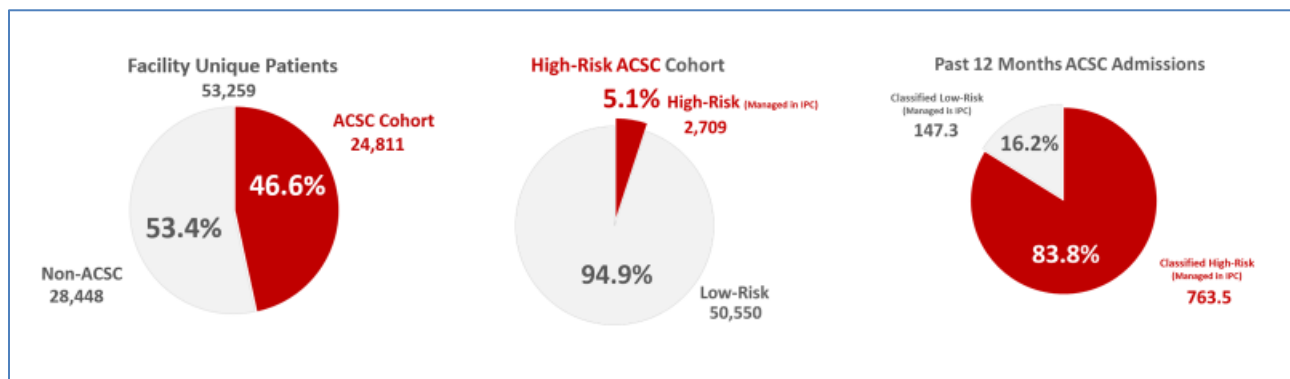
**Figure 3: Sample Scorecard Report from Intelligent Preventive Care Application**

Preventive Care Algorithm	Score (a+b) / n	Cohort (n)	Meeting Algorithm (a)	Reviewed & Removed (b)	Not Reviewed (Opportunity)
6 mth PULMONARY/CHEST visit for high-risk COPD	<b>59%</b>	696	312 (44.8%)	100 (14.4%)	284 (40.8%)
6 mth CARDIOLOGY visit for high-risk CHF	<b>70%</b>	984	526 (53.5%)	167 (17%)	291 (29.6%)
6 mth Mental Health Visit for REACH VET top 0.1% and 1% risk tiers	<b>93%</b>	661	590 (89.3%)	25 (3.8%)	46 (7%)
Scheduled PCP appt for all high-risk patients OR PCP visit in past 100 days for HBPC Teams	<b>78%</b>	2089	1376 (65.9%)	243 (11.6%)	470 (22.5%)

### Making the Case for the Benefits of Operationalizing the Predictive Model

All the hard work on the model and decision support system are for nothing if clinicians and leadership don't buy-in to the product. Figure 4, below, provides an example of how to demonstrate the benefits of using a predictive model. In this case, the model supports the goal of reducing Ambulatory Care Sensitive Condition (ACSC) admissions (such as diabetes or chronic obstructive pulmonary disease), conditions for which outpatient care can potentially prevent the need for hospitalization or for which early intervention can prevent complications or more severe disease. Reducing ACSC admissions is a national performance measure for clinicians and medical centers. Looking at 53,000 patients, it would be difficult to identify who is at risk for ACSC, but applying the predictive model, only 5% are at high risk, accounting for nearly 84% of the ACSC admissions over the past 12 months. The Intelligent Preventive Care model described here can be used to monitor the care for these patients and thus improve this performance measure.

**Figure 4: Using Predictive Modeling Data to Support Reduction in Ambulatory Care Sensitive Conditions (ACSC) Admissions**





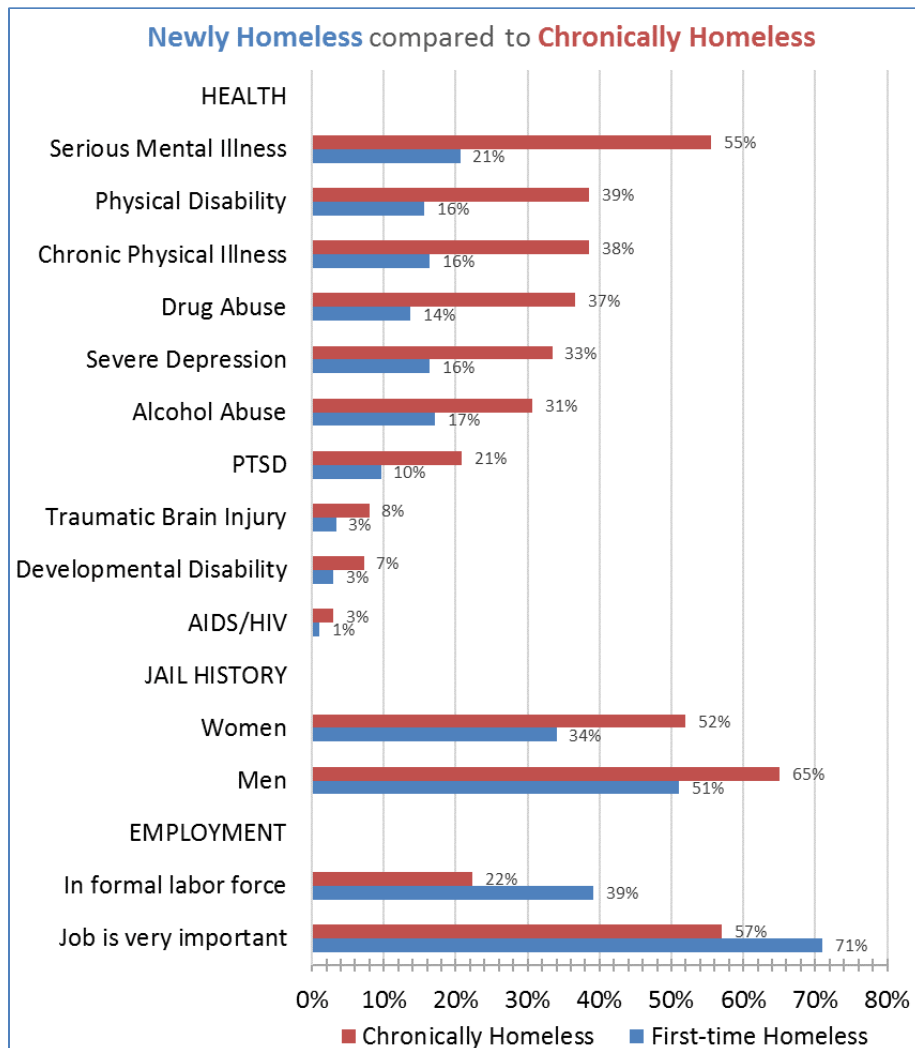
## Using Predictive Analytic Models to Guide Homeless Interventions: Identifying High-Risk Individuals for Intensive Early Intervention

Daniel Flaming, PhD

Shifting to the application of predictive modeling for homeless populations, Daniel Flaming discussed the Economic Roundtable’s development and deployment of two predictive screening tools to identify individuals at high-risk of persistent homelessness in Los Angeles, California: unemployed workers and young adults. Since unemployment is the reason identified most often for loss of housing, the tools are designed to identify people early, when an adult first loses a job and when a youth is just entering adulthood. Those determined to be at risk are offered a comprehensive early intervention, which offers housing, employment training, job placement, and a stipend.

It is crucial to intervene as soon as possible, given that 38% of the people in LA who become homeless stay homeless for over 12 months, with harmful effects. (Figure 5) Many of these individuals will have ongoing, high public costs with negative impacts on their health and well-being: every reported health problem is two to three times more prevalent; incarceration histories increase, particularly among women; and there is less interest in developing skills and finding a job. (3)

Figure 5: Association of Chronic Homelessness with Extensive Harm



The screening tools incorporate 30 to 50 pieces of information to estimate the probability of persistent homelessness within three years. When targeting individuals most at risk, the tools are nine times more accurate than random selection. They are currently being piloted in LA with 33 organizations that provide an array of services for people at risk. As these entities conduct interviews with their clients to collect information about demographics and history of work, mental health, health care, substance use, justice involvement, and homelessness, data relative to the screener are entered into a statistical algorithm that estimates the probability of persistent homelessness. There is an option for a clinical override of the score, at the intake staffer's discretion. Eligible individuals are immediately offered and enrolled in the intervention.

The report and screening tools may be downloaded here. *“Early Intervention to Prevent Persistent Homelessness: Predictive Models for Identifying Unemployed Workers and Young Adults Who Become Persistently Homeless.”*

<https://economicrt.org/publication/early-intervention-to-prevent-persistent-homelessness/>

## **Ethical Challenges in Predictive Analytics for the Care of Homeless Veterans**

**Elizabeth Heitman, PhD**

Elizabeth Heitman outlined some of the complex ethical challenges that emerge for her from the presentations.

Using predictive analytics to shape prevention and intervention for Veterans enrolled in VHA health care involves many of the ethical questions raised by more familiar screening programs. To ensure that the largest population of people at risk of homelessness are captured, the criteria and related decision algorithms need to be inclusive. However, to ensure that only those people at *real* risk of homelessness are identified and included in VHA programs, the criteria and algorithms need to be very specific. There will always be a trade-off between the risk of false positives and false negatives. Where the cutoff is defined is both an issue of data science and a question of justice: Who gets left out? Who gets included in programs that may not benefit them and who may feel coerced or oppressed by the system designed to protect them from harm?

Dr. Fihn raised the important issue of how bias can be introduced into the system. He pointed out that having too little longitudinal data on some patients may give their recent experience disproportionate weight to the calculation of risk. How clinicians and others enter and interpret patient data is also subject to their clinical and personal biases. A number of studies across the US, including in VHA facilities, have shown that the EMR is subject to a variety of inaccuracies stemming from clinicians' habits, such as cutting and pasting text, and technical limitations. Another important limitation in all health records is that clinicians – and even clerical personnel – have unconscious biases about patients' race, age, disease, or overall presentation, which may, in turn, bias how they interpret their need for care. This implicit bias disproportionately affects the care of already vulnerable populations, like the homeless. Systems for predictive analytics will need to guard against assuming that all data in the EMR are “objective,” since the algorithms they create will standardize criteria that may institutionalize bias.

## Recommendations

Predictive analytics are here to stay. Good models with highly predictive statistics are being built and used to make risk estimates. The presentations and roundtable discussion yield the following recommendations for consideration in developing and implementing these tools.

- ❖ Predictive modeling is as much an art as a science. In developing predictive analytic models, look at all the data available and test as many variables as possible, especially those that are standardized.
- ❖ Establish an infrastructure to provide oversight and review of AI tools to ensure that issues around ethics and fairness are addressed, such as possible bias in the data elements that are included or excluded.
- ❖ Predictive models are only as helpful as the clinical practices in which they are embedded. Models need to be conceptualized as parts of clinical processes or interventions that improve the quality and safety of health care systems. They should be designed to produce information that will target interventions to the people most likely to benefit from them and to facilitate the coordination of care among clinicians so that patients will be directed to the places and people who can best serve them.
- ❖ When implementing a predictive model in a health system it is important to consider all of the governance issues involved. These include organizational capabilities, personnel capacity, cost, cybersecurity and privacy, ethics and fairness, safety and efficacy surveillance, and regulatory issues.
- ❖ Predictive models should be tested through clinical trials.
- ❖ Predictive screening tools should be developed to maximize people's potentials – to give something to people at risk rather than take something away.

## References

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4. Source: Los Angeles Homeless Services Authority (LAHSA): 2016 and 2017 demographic surveys of unsheltered individuals.

## Participant Biographies



**Stephan Fihn**, MD, MPH is a Professor of Medicine and Health Services and Division Head of General Internal Medicine at the University of Washington. He was a general internist, staff physician, and HSR&D researcher with VA for 36 years until his retirement in 2018. His research addressed a broad range of topics related to strategies for improving the efficiency and quality of primary medical care and understanding the epidemiology of common medical problems. One of his most important contributions was helping to create the Clinical Assessment, Reporting, and Tracking System for Cardiac Catheterization Laboratories (CART-CL). The CART-CL clinical application is now integrated within VA's computerized patient record system, allowing for standardized data capture and reporting across all VA cath labs.



**Daniel Flaming**, PhD, is president of the Economic Roundtable, a nonprofit urban research group that identifies actionable solutions for improving community well-being. The Roundtable's work includes descriptive analysis of homelessness as a dynamic problem and also developing predictive analytic tools for differentiating level of risk among homeless individuals. Daniel has been with the Roundtable since 1991. Before that he worked for Los Angeles County, managing delinquency prevention, affordable housing, job training, and research programs.



**Elizabeth Heitman**, PhD, is Professor in the Program in Ethics in Science and Medicine at the University of Texas Southwestern Medical Center in Dallas. Her work focuses on cultural aspects of ethics in clinical medicine, public health, biomedical science, and particularly international standards of research ethics and education in the responsible conduct of research (RCR). She teaches research ethics and RCR in the Center for Translational Medicine and graduate school and is an ethics facilitator for medical students. Dr. Heitman has been an educator, researcher, and clinical ethics consultant for almost 30 years, and was previously on the faculty at Vanderbilt University Medical Center and the University of Texas – Houston Health Science Center (now UT Health).



**Dina Hooshyar**, MD, MPH is Director of the National Center on Homelessness among Veterans. With a background in internal medicine, psychiatry, and public health, she has served in the US Public Health Service Commissioned Corps; worked as Medical Director of VA North Texas Health Care System Mental Health Service's Comprehensive Homeless Center Programs; and held the position of Physician Advisor in VA North Texas Health Care System's Chief of Staff Office. Dr. Hooshyar is also an Associate Professor at the University of Texas Southwestern Medical Center.



**James Marquez**, MBA, is a Data Scientist from the VA Hudson Valley Health Care System in New York working remotely from Southern California. Strengths include operationalizing health care predictive models through building custom web applications, such as the Intelligent Preventive Care (IPC) web application currently in use at 66 VA facilities, and Python and R statistical programming.



**Jodie Trafton**, PhD, is the Director of the Program Evaluation and Resource Center in the Office of Mental Health and Suicide Prevention at the Veterans Health Administration (VHA) and an affiliated Clinical Professor at Stanford University in the Department of Psychiatry and Behavioral Sciences. Dr. Trafton directs a team that implements new mental health care interventions and delivery models across VHA's 141 health care systems. As one component of implementation efforts, her team builds informatics tools to enable, structure and incentivize management and clinical decisions and practices included in best practice models.