Methods: Mind the Gap Webinar Series

Suicide Prevention Enabled by Data Science

Presented by

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Suicide Prevention Enabled by Data Science

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January 24th, 2019

Disclosures

No relevant disclosures, financial or otherwise

Objectives

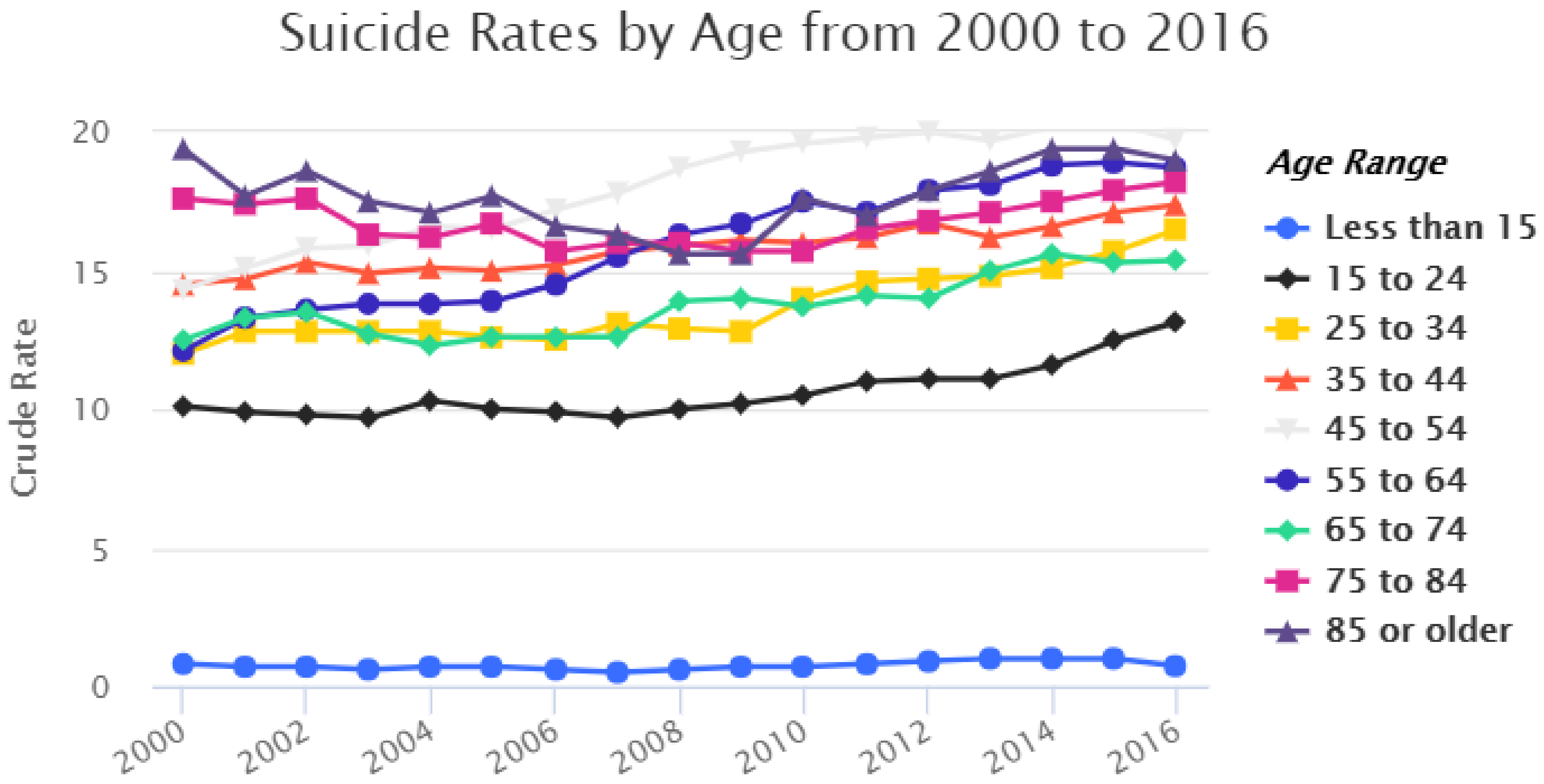
- To discuss active efforts in data science for suicide prevention
- To review ongoing collaborations to implement predictive models at point of care
- To describe challenges in this domain including ethics and -omics

Background

- Today, 123 Americans will die from suicide (10th leading cause of death in the U.S.)

- In a given year, 1 in 40 Americans will attempt suicide

- 1 in 20 will contemplate suicide

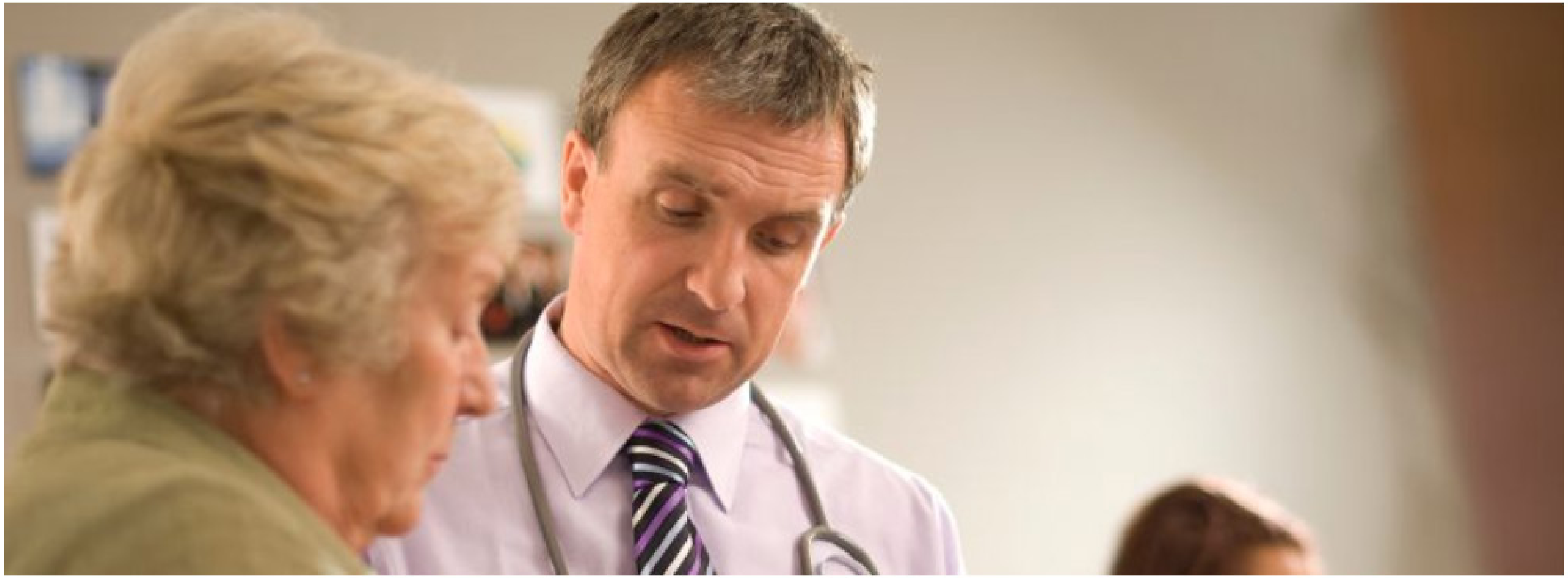


American Foundation of Suicide Prevention

Also in This Section

Comprehensive Approach
- Identify and Assist
- Increase Help-Seeking
- Effective Care/Treatment
- Care Transitions/Linkages
- Respond to Crisis
- Postvention
- Reduce Access to Means
- Life Skills and Resilience
- Connectedness

Identify and Assist Persons at Risk



Identifying persons who may be at risk for suicide is a key part of a comprehensive approach to suicide prevention. Family members, friends, teachers, coaches, coworkers, and others can play an important role in recognizing when someone is at risk or in crisis and then connecting that person with the most appropriate sources of care. But these individuals may need training on how to identify suicide risk and provide assistance.

Background

- 24% of 6,000 deaths had no mental health diagnosis in the medical record in the year before death (MHRN)
- Only 3% of those with suicidal ideation documented in primary care notes also had a diagnostic code (Anderson et al, J Am Board Fam Med, 2015)

Background

- Increased **availability** of tools to extract meaningful signal from complex healthcare data
- Growing appetite for **collaboration** and data sharing in medicine
- Advanced **understanding** of risk factors preceding suicidal behaviors

Examples

Methods

Background – A Modeling Primer

1. Study Design
2. Data Extraction and Cleaning
3. Predictor/Feature Selection and Transforms
4. Prediction and Validation
5. Iteration

Overview of Methods

Predicting Risk of Suicide Attempts Over Time Through Machine Learning

Clinical Psychological Science
1–12
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sagepub.com/journalsPermissions.nav
DOI: 10.1177/2167702617691560
cpx.sagepub.com
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Overview and Examples of EHR-based Predictive Modeling

- Define outcome(s) and cohort(s) of interest
  - Outcome – suicide attempt confirmed via chart review
  - Cohort – adults receiving routine care at Vanderbilt

- Determine sample size(s) from existing data
  - Cases – 3,250 adults with confirmed suicide attempts
  - Controls – 13,000 adults with > 3 visits over 6 months at Vanderbilt

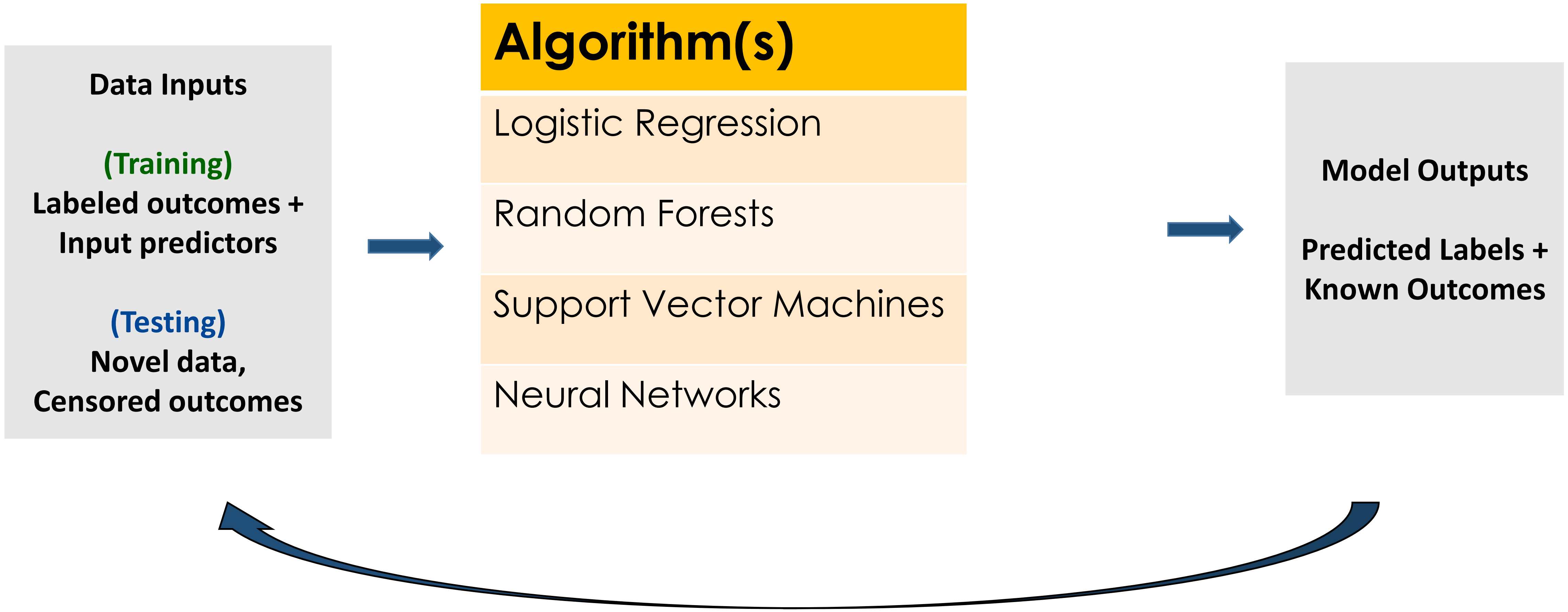
  Or
  - Only those with depression in problem lists

  Or
  - Only those seen in an Emergency Department

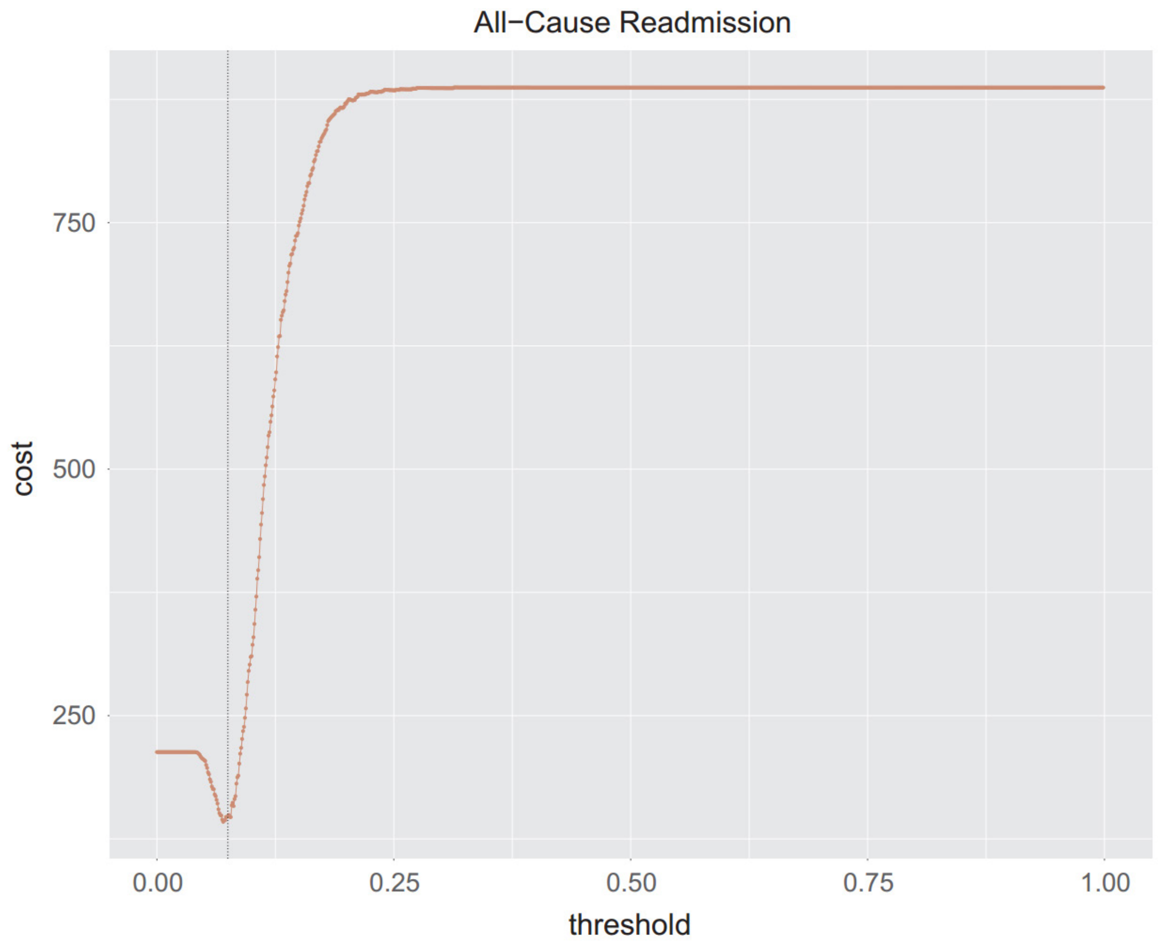
- Select potential predictors using expert knowledge, literature, and understanding of data sources

Overview and Examples of EHR-based Predictive Modeling

- Select potential predictors using expert knowledge, literature, and understanding of data sources
  - Diagnoses
  - Medications
  - Visit Utilization, e.g., #s of outpatient, inpatient, emergency visits
  - Demographics, e.g., age, Race, Sex
  - Socioeconomic Status and Support, e.g., Marital Status, Zip Code (mapped to Area Deprivation Index)


Data Inputs
(Training)
Labeled outcomes +
Input predictors
(Testing)
Novel data,
Censored outcomes
Algorithm(s)
Logistic Regression
Random Forests
Support Vector Machines
Neural Networks
Model Outputs
Predicted Labels +
Known Outcomes

Performance Evaluation

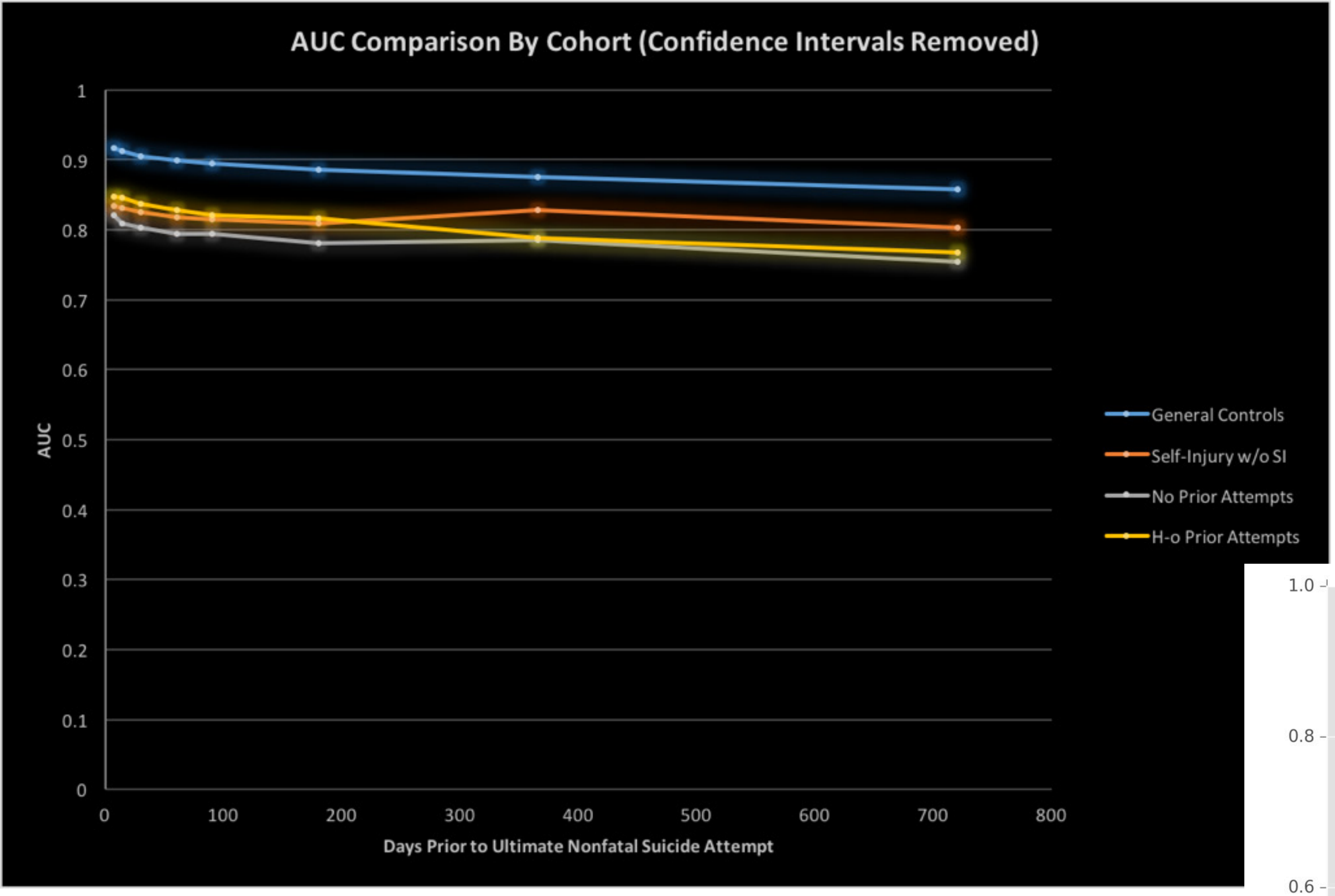


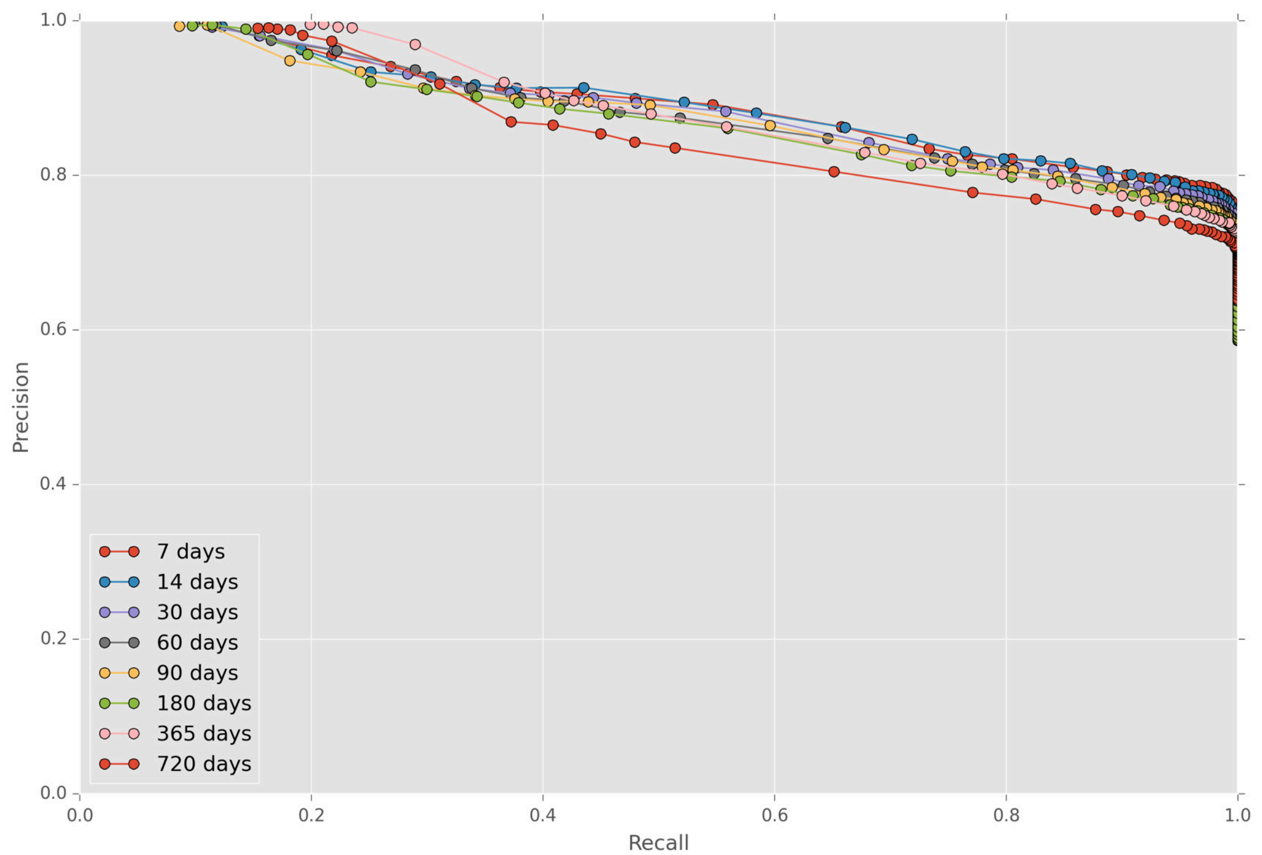
- Discrimination – Separate "Cases" from "Controls"
- Calibration – predictions reflect true prevalence
- Usefulness – what are the benefits and harms of these models in practice

Beyond discrimination: A comparison of calibration methods and clinical usefulness of predictive models of readmission risk

Colin G. Walsh[a,b,c,*], Kavya Sharman[a], George Hripcsak[d]

http://dx.doi.org/10.1016/j.jbi.2017.10.008


AUC Comparison By Cohort (Confidence Intervals Removed)
AUC
Days Prior to Ultimate Nonfatal Suicide Attempt
General Controls
Self-Injury w/o SI
No Prior Attempts
H-o Prior Attempts
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
100
200
300
400
500
600
700
800


Precision
Recall
7 days
14 days
30 days
60 days
90 days
180 days
365 days
720 days
0.0
0.2
0.4
0.6
0.8
1.0

Next Steps after Initial Validation of a Model

- Does it work in new [cohorts/outcomes/settings]?
- How will it be deployed and evaluated? How does it augment clinical workflow?
- What are the potential benefits and harms of integrating modeling into clinical practice?

New Age Groups, e.g., Adolescents

Attention Deficit Disorders

Environment

Comorbid Illness

PTSD

The Journal of Child Psychology and Psychiatry

Journal of Child Psychology and Psychiatry **:* (2018), pp **–** doi:10.1111/jcpp.12916

Predicting suicide attempts in adolescents with longitudinal clinical data and machine learning

Colin G. Walsh,[1] Jessica D. Ribeiro,[2] and Joseph C. Franklin[2]

[1]Vanderbilt University Medical Center, Nashville, TN; [2]Florida State University, Tallahassee, FL, USA

Images from Cleveland Clinic.org (Left) and nytimes.com (Right)

New Cohorts, e.g., Chronic Pain, Fibromyalgia

- 14,000 VUMC patients with Fibromyalgia by PheKB Definition (Doss et al, 2017)
- True external validation: predict Suicidal Thoughts (AUC 0.8) and Behaviors (AUC 0.82) in a new cohort with prior model
- But can we **explain** this performance and might it suggest intervention?



McKernan, Lenert, Crofford, Walsh, Arthritis Care Res, 2018
https://doi.org/10.1002/acr.23748

New Cohorts, e.g., Chronic Pain and Fibromyalgia

- We can use a variation on the LASSO, the BoLASSO, to rigorously select predictors
- Predictors can be tested for strength of effect and direction (Added Risk? Protective?)

New Risk Factors Unique to FM:

- Polysomatic: “Fatigue”, “Dizziness”, “Abdominal Pain”
- Comorbid Psychiatric and Medical Illness
- Frequent Inpatient Admission, Lack of Outpatient Visits

https://doi.org/10.1002/acr.23748

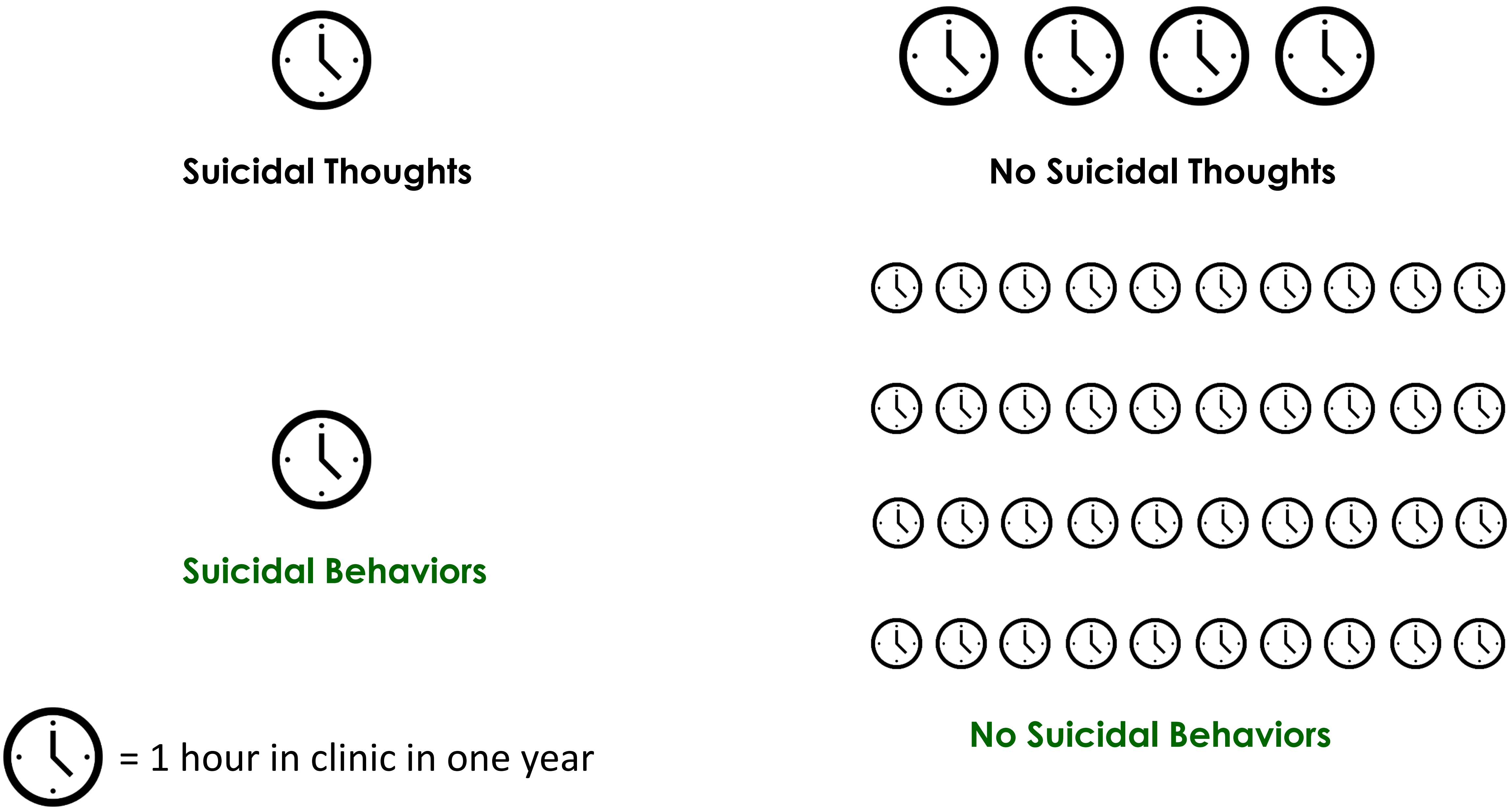
New Cohorts, e.g., Chronic Pain and Fibromyalgia

- Protective Factors Driven by Outpatient Care and Medication Prescription

- Time-Based Utilization Analysis

- **For every hour spent in clinic by those with Suicidal Thoughts and Behaviors (SITBs), how many were spent by those who never presented with SITBs?**

https://doi.org/10.1002/acr.23748



https://doi.org/10.1002/acr.23748

New Insights – Genetics of Suicide Attempt

Molecular Psychiatry
https://doi.org/10.1038/s41380-018-0326-8

ARTICLE

Check for updates

Significant shared heritability underlies suicide attempt and clinically predicted probability of attempting suicide

Douglas M. Ruderfer[1,2] · Colin G. Walsh[2] · Matthew W. Aguirre[3] · Yosuke Tanigawa[3] · Jessica D. Ribeiro[4] · Joseph C. Franklin[4] · Manuel A. Rivas[3]

Received: 4 June 2018 / Revised: 15 September 2018 / Accepted: 12 November 2018
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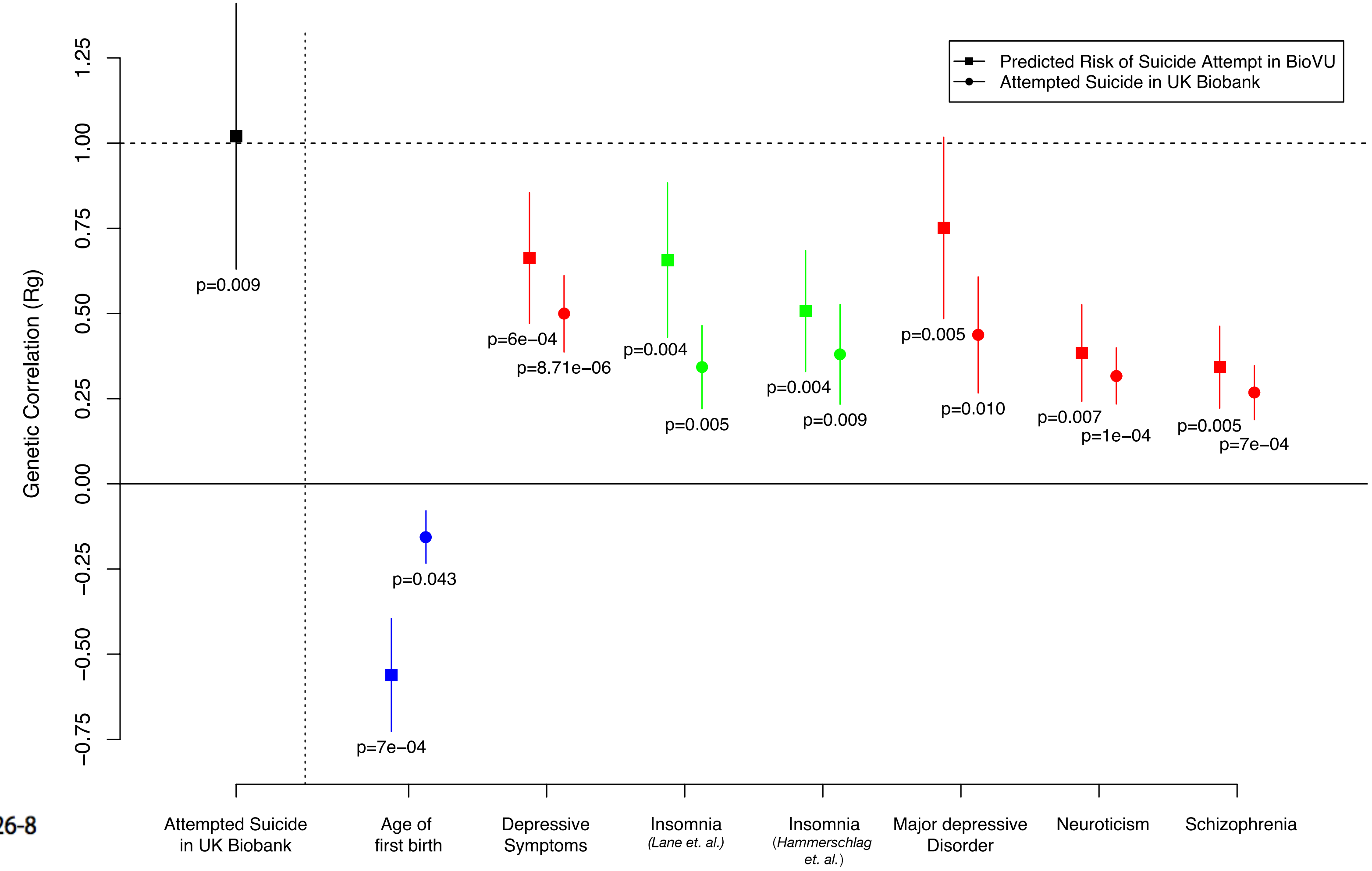
Genetic Risk of Suicide Attempt

Suicide Attempt Risk is **4% Heritable**



Molecular Psychiatry
https://doi.org/10.1038/s41380-018-0326-8

From Prediction to Practice

Suicide Prevention Decision Support at Vanderbilt University Medical Center

Prospective Validation using operational systems at Vanderbilt

Clinical Process Design to understand best current practices and enable prevention

Adhere to **Plan**, **Test**, **Pilot**, **Deploy**

Evelyn Selby Stead Fund for Innovation Grant

From Civilian Risk to Active Duty

Aim 1: Validate and Update our Models in the U.S. Navy Active Duty Servicemembers

Aim 2: Evaluate Clinical Routines and Workflows to Inform CDS

Aim 3: Pilot Decision Support and Study Uptake and Behaviors



Military Suicide Research Consortium
Grant #W81XWH-10-2-0181

Translation of Risk Prediction into Practice
(Haroz, Cwik, Barlow,… Walsh, AAS, 2018)

- Community-based Healthcare for Native Americans in the American Southwest
- Case Workers Provide Care and Record Data from Clinical Encounters in Structured Forms
- mHealth Care Delivery Framework

JOHNS HOPKINS
CENTER FOR AMERICAN INDIAN HEALTH

Celebrating Life Suicide Prevention Program

- Community based suicide surveillance and case management program

- Tribally mandated reporting of the following behaviors to surveillance system
  1) suicidal thoughts
  2) binge-drinking
  3) self-injurious behavior
  4) suicide attempt
  5) suicide death

- No routine EHR data here, only what is collected by case workers

Celebrating Life – Key Results

- AUC 0.83 to predict suicide attempts or death at two years using ML on case data
- Refining and **simplifying** algorithms for implementation, our current effort (NIMH U19 MH113136-02S3)
- Needs to be 1) mobile; 2) off-line (sometimes); 3) interpretable

Grand Challenges – Data Scientific

- Causal inference
- Time
- Low Precision and rare events

Grand Challenges – Clinical

- Clinical effectiveness
- Better engaging patients and their loved ones
- Contextualizing prediction into prevention
- Avoiding worsened stigma

Privacy Concerns

Enabling Open-Science Initiatives in Clinical Psychology and Psychiatry Without Sacrificing Patients' Privacy: Current Practices and Future Challenges

Colin G. Walsh , Weiyi Xia , Muqun Li , Joshua C. Denny , Paul A. Harris , Bradley A. Malin Show less

First Published January 23, 2018 | Research Article | Check for updates

Advances in Methods and Practices in Psychological Science aps | ASSOCIATION FOR PSYCHOLOGICAL SCIENCE

PERSPECTIVE ARTICLE

Front. Psychiatry, 03 December 2018 | https://doi.org/10.3389/fpsyt.2018.00650

Protecting Life While Preserving Liberty: Ethical Recommendations for Suicide Prevention With Artificial Intelligence

Lindsey C. McKernan[1,2*], Ellen W. Clayton[3,4] and Colin G. Walsh[1,5,6]

frontiers in Psychiatry

Domain	Recommendation for implementation	Recommendation for research
Consent	Develop informed consent for patients to sign detailing the actions and limitations of AI	Develop consent forms to all literacy levels and test for understanding
	Develop similar consent for providers	Develop patient education materials that detail the purpose of AI and evaluate for understanding
	Provide patients with "opt-out" of AI monitoring	
	Provide time limits or expiration to consent	
	Re-consent each year with evolving technology	
	Have consent documents approved by experts and medical review board	
Controls	Adopt standards for suicide monitoring with AI, such as determining what percentage of at-risk individuals will be monitored	Compare provider-informed vs. AI-only model to assess for increased accuracy with feedback
	Form an AI oversight panel with multidisciplinary specialty	
	Request provider feedback routinely and update systems accordingly	
	Create a system for providers to defer or activate risk monitoring with explanation	
	Log model successes and failures, re-train models	
Communication	Conduct focus groups with stakeholders to assess for appropriateness and utility of integrating AI into healthcare	Develop provider materials and elicit feedback for appropriateness
	Provide communication materials for provider use to discuss AI and the monitoring process	

https://doi.org/10.3389/fpsyt.2018.00650

From Prediction to Prevention Strategies

- Combining data science with explanatory approaches may suggest intervention

- May also improve uptake

Mediation of adoption and use: a key strategy for mitigating unintended consequences of health IT implementation

Laurie L Novak,[1] Shilo Anders,[2] Cynthia S Gadd,[1] Nancy M Lorenzi[1]

J Am Med Inform Assoc 2012;**19**:1043–1049. doi:10.1136/amiajnl-2011-000575

Primary Findings

- Scalable, robust models with great reach
- Unprecedented quantities and combinations of data
- Unprecedented willingness for cross-cutting collaboration
- Many unanswered questions on how these tools integrate optimally into practice

Limitations

- Biases abound – sampling, clinical, anchoring
- Reliance on published algorithms
- Reliance on supervised approaches
- Reliance on secondary use – “data we have, but is it the data we need?”

Future Directions

- Partnering to trial prevention strategies
- Optimizing the “Five Rights” of decision support
- Integrating genetics into clinical prevention
- And more…

Acknowledgements

JOHNS HOPKINS UNIVERSITY

CENTER FOR AMERICAN INDIAN HEALTH

UNITED STATES NAVY

VANDERBILT UNIVERSITY MEDICAL CENTER

FLORIDA STATE UNIVERSITY 1851 VIRES ARTES MORES

Stanford University

Acknowledgements

Walsh Lab

- Matthew Lenert, Lina Sulieman, John Shelley, Malia Latimer, Chris Puchi, Michael Ripperger

VUMC Collaborators and Mentors

- Lindsey McKernan, Leslie Crofford, Douglas Ruderfer, Laurie Novak, Steven Johnson, Christopher Simpson, Weiyi Xia, Muqun Li, Steve Nyemba, Josh Denny, Brad Malin, Paul Harris, Kevin Johnson

FSU Collaborators

- Joseph Franklin, Jessica Ribeiro

JHU Collaborators

- Emily Haroz, Alison Barlow, Emily Cwik

Stanford Collaborators

- Manual Rivas, Matthew Aguirre

Funding Sources

W81XWH-10-2-0181

Evelyn Stead Center for Innovation Fund

R01 LM010685-09S1

U19MH113136-02S3

DBMI Support

Questions?

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