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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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
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.

Supporting a Suicide Risk
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

- Study Design
- Data Extraction and Cleaning
- Predictor/Feature Selection and Transforms
- Prediction and Validation
- Iteration
Overview of Methods

Predicting Risk of Suicide Attempts Over Time Through Machine Learning

Colin G. Walsh1,2,3, Jessica D. Ribeiro4, and Joseph C. Franklin4
1Department of Biomedical Informatics, Vanderbilt University Medical Center; 2Department of Medicine, Vanderbilt University Medical Center; 3Department of Psychiatry, Vanderbilt University Medical Center; and 4Department of Psychology, Florida State University
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)
<table>
<thead>
<tr>
<th>Algorithm(s)</th>
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<tbody>
<tr>
<td>Logistic Regression</td>
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<td>Random Forests</td>
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<td>Support Vector Machines</td>
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<td>Neural Networks</td>
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Data Inputs

*(Training)*
Labeled outcomes + Input predictors

*(Testing)*
Novel data, Censored outcomes

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, Kavya Sharman, George Hripcsak

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

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
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?
Suicidal Thoughts

= 1 hour in clinic in one year

No Suicidal Thoughts

Suicidal Behaviors

No Suicidal Behaviors

https://doi.org/10.1002/acr.23748
Significant shared heritability underlies suicide attempt and clinically predicted probability of attempting suicide

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

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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
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


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

First Published January 23, 2018 | Research Article

Advances in Methods and Practices in Psychological Science
Protecting Life While Preserving Liberty: Ethical Recommendations for Suicide Prevention With Artificial Intelligence

Lindsey C. McKernan, Ellen W. Clayton and Colin G. Walsh
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<tr>
<th>Domain</th>
<th>Recommendation for implementation</th>
<th>Recommendation for research</th>
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<tr>
<td><strong>Consent</strong></td>
<td>Develop informed consent for patients to sign detailing the actions and limitations of AI</td>
<td>Develop consent forms to all literacy levels and test for understanding</td>
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<td>Develop similar consent for providers</td>
<td>Develop patient education materials that detail the purpose of AI and evaluate for understanding</td>
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<td>Provide patients with “opt-out” of AI monitoring</td>
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<td>Provide time limits or expiration to consent</td>
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<td>Re-consent each year with evolving technology</td>
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<td>Have consent documents approved by experts and medical review board</td>
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<td><strong>Controls</strong></td>
<td>Adopt standards for suicide monitoring with AI, such as determining what percentage of at-risk individuals will be monitored</td>
<td>Compare provider-informed vs. AI-only model to assess for increased accuracy with feedback</td>
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<td>Form an AI oversight panel with multidisciplinary specialty</td>
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<td>Request provider feedback routinely and update systems accordingly</td>
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<td>Create a system for providers to defer or activate risk monitoring with explanation</td>
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<td>Log model successes and failures, re-train models</td>
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<td><strong>Communication</strong></td>
<td>Conduct focus groups with stakeholders to assess for appropriateness and utility of integrating AI into healthcare</td>
<td>Develop provider materials and elicit feedback for appropriateness</td>
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<td>Provide communication materials for provider use to discuss AI and the monitoring process</td>
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https://doi.org/10.3389/fpsyg.2018.00650
From Prediction to Prevention Strategies

• Combining data science with explanatory approaches may suggest intervention

• May also improve uptake
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...
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Questions?

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