The Importance of Algorithmic Explainability in Behavioral Health

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Objectives

• To highlight the relevance of explainability to behavioral and mental health

• To provide examples of studies to bridge those gaps

• To suggest key topics in this area for discussion
Background

• Today, 123 Americans will die from suicide

• Yearly, 1 in 40 Americans attempt suicide

• 1 in 20 contemplate suicide

Active-Duty Military Suicides at Record Highs in 2018

Lt. Cmdr. Karen Downer writes a name on a Suicide Awareness Memorial Canvas in honor of Suicide Awareness Month at Naval Hospital Jacksonville, Sept. 10, 2018. (U.S. Navy/Jacob Sippel, Naval Hospital Jacksonville).
Suicide Risk Stratification and Prediction

Machine Intelligence + Routine Healthcare Data
Explainability and Accuracy
Prediction != Prevention

Machines know when someone’s about to attempt suicide. How should we use that information?

By Olivia Goldhill • September 5, 2018
The Why of Explainability

• All models are wrong, some are useful*

• But in behavioral health, errors might lead to:
  • Harm or loss of life
  • Unnecessary treatment or threats to liberty interest
  • Stigma
  • Negative career impacts
  • Loss of trust for both patients and providers

Predicting Risk of Suicide Attempts Over Time Through Machine Learning

Colin G. Walsh, Jessica D. Ribeiro, and Joseph C. Franklin

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

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

Lindsay C. McKernan, Ellen W. Clayton, and Colin G. Walsh

Outpatient Engagement Lowers Predicted Risk of Suicide Attempts in Fibromyalgia

Lindsey C McKernan, Matthew C Lenert, Leslie J Crofford, Colin G Walsh

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

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

Balancing Performance and Interpretability: Selecting Features with Bootstrapped Ridge Regression

Matthew C. Lenert, BA and Colin G. Walsh, MD MA
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Colin G. Walsh¹,₂,³, Jessica D. Ribeiro⁴, and Joseph C. Franklin¹

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

Douglas M. Ruderfer⁵,⁶, Colin G. Walsh⁵, Matthew W. Aguirre⁵, Yosuke Tanigawa⁵, Jessica D. Ribeiro⁴, Joseph C. Franklin⁵, Manuel A. Rivas³

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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
Can we see into the algorithm’s black box?

- 14,000 Vanderbilt patients with Fibromyalgia
- Our predictive algorithms “work” in this group (aka external validation)
- But can we explain this performance and might it suggest intervention?
Can we see into the algorithm’s black box?

- Protective Factors Driven by Outpatient Care and Medication Prescription
- Time-Based Utilization Analysis

Possible Intervention

[Image of article: Outpatient Engagement Lowers Predicted Risk of Suicide Attempts in Fibromyalgia]

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**Balancing Performance and Interpretability: Selecting Features with Bootstrapped Ridge Regression**

Matthew C. Lenert, BA, Colin G. Walsh, MD MA (Primary Advisor)
Explainability and the “Five Rights”

• the right information,
• to the right person,
• in the right intervention format,
• through the right channel,
• at the right time in workflow.
Open Questions and Gaps

• Explainable does not equal Actionable

• When does Explainability matter most? When might it not matter?

• Interpretability of an algorithm is not the same as insights about an individual

• Explainability is not causality
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