Suicide Prevention and the Necessity of Scientific Revolution

Robert M. Bossarte, PhD
Director, Injury Control Research Center
Associate Professor, Department of Psychiatry and Behavioral Medicine
West Virginia University
Acknowledgements

• Cara Mangine, MPH
• Sara Warfield, MPH
• Shannon Barth, MPH

Supported by Grant Number: 1R49CE002109 from the Centers for Disease Control and Prevention, National Center for Injury Prevention and Control, to the West Virginia University Injury Control Research Center. The contents are solely the responsibility of the authors and do not necessarily represent the official views of the Centers for Disease Control and Prevention.
Thomas Kuhn and Scientific Assumptions

- A *scientific community* cannot practice its trade without some set of *received beliefs*.
  - These beliefs form the foundation of the "educational initiation that prepares and licenses the student for professional practice".
  - The nature of the "rigorous and rigid" preparation helps ensure that the received beliefs exert a "deep hold" on the student's mind.
- *Normal science* "is predicated on the assumption that the scientific community knows what the world is like"—scientists take great pains to defend that assumption.
- To this end, "normal science often suppresses fundamental novelties because they are necessarily subversive of its basic commitments".
- *Research* is "a strenuous and devoted attempt to force nature into the conceptual boxes supplied by professional education".
- A *shift* in professional commitments to shared assumptions takes place when an *anomaly* "subverts the existing tradition of scientific practice". These shifts are what Kuhn describes as *scientific revolutions*—"the tradition-shattering complements to the tradition-bound activity of normal science".
  - New assumptions (paradigms/theories) require the reconstruction of prior assumptions and the reevaluation of prior facts. This is difficult and time consuming. It is also strongly resisted by the established community.
  - When a shift takes place, "a scientist's world is qualitatively transformed [and] quantitatively enriched by fundamental novelties of either fact or theory".

Source: “The Structure of Scientific Revolutions”, Frank Pajares, Emory University
Anomaly and the Emergence of Scientific Discovery

- Normal science does not aim at novelties of fact or theory and, when successful, finds none.
- Nonetheless, new and unsuspected phenomena are repeatedly uncovered by scientific research, and radical new theories have again and again been invented by scientists.
- Fundamental novelties of fact and theory bring about paradigm change.
- So how does paradigm change come about?
  - Discovery—novelty of fact.
  - Invention—novelty of theory.

- The process of paradigm change is closely tied to the nature of perceptual (conceptual) change in an individual—**Novelty emerges only with difficulty, manifested by resistance, against a background provided by expectation.**
- Although normal science is a pursuit not directed to novelties and tending at first to suppress them, it is nonetheless very effective in causing them to arise. Why?
  - An initial paradigm accounts quite successfully for most of the observations and experiments readily accessible to that science's practitioners.
  - Research results in
    - the construction of elaborate equipment,
    - development of an esoteric and shared vocabulary,
    - refinement of concepts that increasingly lessens their resemblance to their usual common-sense prototypes.
  - This professionalization leads to
    - immense restriction of the scientist's vision, rigid science, and resistance to paradigm change.
    - a detail of information and precision of the observation-theory match that can be achieved in no other way.
  - Consequently, **anomaly appears only against the background provided by the paradigm.**
    - The more precise and far-reaching the paradigm, the more sensitive it is to detecting an anomaly and inducing change.
    - By resisting change, a paradigm guarantees that anomalies that lead to paradigm change will penetrate existing knowledge to the core.

Source: “The Structure of Scientific Revolutions”, Frank Pajares, Emory University
Assumptions Underlying Suicide Research

1. Risk for suicide is the result of a combination of baseline biological and psychological vulnerability and environmental stressors.
2. Risk for suicide progresses along a linear path.
3. Suicide can be understood (and prevented) using standard medical models.
4. Suicide risk is uniquely the result of mental illness.
5. Prevention begins with the identification of persons at high risk.
6. Suicide risk is a dynamic state that can be reliably measured.
7. Suicide risk can be distinguished from risk for other adverse outcomes.
8. Clinical care is the pathway to prevention.
9. Risk for suicide is the target for prevention.
What Happens When We Fail to Consider our Assumptions?

• Alternative paradigms, or challenges or the existing paradigm, are not considered – in other words, “normal science” continues.

• We may fail to foresee the unintended consequences of our activities.

• However, Kuhn suggested that “normal” science was necessary for scientific revolution and that paradigm shifts were inevitable when the existing knowledge base is incapable of answering new questions.
  – Have we reached the point of revolution in suicide prevention?
Rates of Suicide, United States 1981 – 2015

The National Strategy was revised to reflect major developments in suicide prevention, research, and practice during the past decade. Examples include the following.

1. An increased understanding of the link between suicide and other health issues. Research confirms that health conditions such as mental illness and substance abuse, as well as traumatic or violent events can influence a person’s risk of suicide attempts later in life. Research also suggests that connectedness to family members, teachers, coworkers, community organizations, and social institutions can help protect individuals from a wide range of health problems, including suicide risk.

2. New knowledge on groups at increased risk. Research continues to suggest important differences among various demographics in regards to suicidal thoughts and behaviors. This research emphasizes that communities and organizations must specifically address the needs of these communities when developing prevention strategies.

3. Evidence of the effectiveness of suicide prevention interventions. New evidence suggests that a number of interventions, such as behavior therapy and crisis lines, are particularly useful for helping individuals at risk for suicide. Social media and mobile apps provide new opportunities for intervention.

4. Increased recognition of the value of comprehensive and coordinated prevention efforts. Combining new methods of treating suicidal patients with a prompt patient follow-up after they have been discharged from the hospitals is an effective suicide prevention method.

Source: National Strategy for Suicide Prevention, Goals and Objectives
Predictive Modeling and Concentration of the Risk of Suicide: Implications for Preventive Interventions in the US Department of Veterans Affairs

John F. McCarthy, PhD, Robert M. Bossarte, PhD, Ira R. Katz, MD, PhD, Caitlin Thompson, PhD, Janet Kemp, PhD, Claire M. Hannemann, MPH, Christopher Nielson, MD, and Michael Schoenbaum, PhD

Over the past 8 years, the Veterans Health Administration (VHA), the health system of the Department of Veterans Affairs, strengthened its mental health services and supplemented them with specific programs for suicide prevention. However, suicide rates in VHA have been stable, without decreases that can be attributed to these enhancements. The table...

Objectives. The Veterans Health Administration (VHA) evaluated the use of predictive modeling to identify patients at risk for suicide and to supplement ongoing care with risk-stratified interventions.

Methods. Suicide data came from the National Death Index. Predictors were measures from VHA clinical records incorporating patient-months from October 1, 2008, to September 30, 2011, for all suicide decedents and 1% of living patients, divided randomly into development and validation samples. We used data on all patients alive on September 30, 2010, to evaluate predictions of...
Methods

• Case-Control Design
  – Month by month identification of cases (suicide decedents) and sample of controls (non-decedents) for each of 36 consecutive months: FY2009-FY2011
  – Inclusion criterion: Patients had to have had some VHA encounters in the prior 24 months
  – Of these recent VHA users, who did we include?
    • All suicides (6360 suicides over the 36 month period)
    • 1% sample of controls (2,112,008 controls over 36 months)
Goals

• Identify VHA patients with the greatest suicide risk concentration
  – Develop logistic regression models of suicide risk among VHA patients
    • Quantify suicide risk based on clinical/administrative data
    • Validate models
    • Assess predictive power of these profiles
  – Develop interventions for those at high risk
    • Care management for those at the highest risk
      – Most direct way to save lives
      – But it will not “bend the curve”
    • More public health-oriented models for those at lower levels of increased risk
      – May involve less direct clinical intervention
      – But it may have a greater impact on the population
Validation

1. Split samples
   How does model-predicted risk relate to suicide mortality in the hold-out (Model Validation) dataset?
   **Half sample:** Model Development dataset
   **Half sample:** Model Validation dataset

2. “Prediction Cohort” (ALL VHA patients who were alive at end of September 2010 and had had VHA use in prior 24 months; N = 5,969,882)
   How does model-predicted risk relate to suicide mortality and all-cause mortality in next months (up to 12 months)?
## Risk Stratification

**Development Sample**

**All patients**

<table>
<thead>
<tr>
<th>Top Proportion</th>
<th>Total</th>
<th>Cases</th>
<th>Total Cases</th>
<th>Percent Cases</th>
<th>Ratio of Percent Cases to Expected Percent</th>
<th>Annualized Suicide Rate per 100,000 person-years</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0001</td>
<td>21,120</td>
<td>60</td>
<td>6360</td>
<td>0.9%</td>
<td>94.34</td>
<td>3,409.09</td>
</tr>
<tr>
<td>0.0005</td>
<td>105,604</td>
<td>166</td>
<td>6360</td>
<td>2.6%</td>
<td>52.20</td>
<td>1,886.29</td>
</tr>
<tr>
<td>0.001</td>
<td>211,208</td>
<td>248</td>
<td>6360</td>
<td>3.9%</td>
<td>38.99</td>
<td>1,409.04</td>
</tr>
<tr>
<td>0.005</td>
<td>1,056,044</td>
<td>620</td>
<td>6360</td>
<td>9.7%</td>
<td>19.50</td>
<td>704.52</td>
</tr>
<tr>
<td>0.01</td>
<td>2,112,088</td>
<td>890</td>
<td>6360</td>
<td>14.0%</td>
<td>13.99</td>
<td>505.66</td>
</tr>
<tr>
<td>0.05</td>
<td>10,560,440</td>
<td>1986</td>
<td>6360</td>
<td>31.2%</td>
<td>6.25</td>
<td>225.67</td>
</tr>
<tr>
<td>0.1</td>
<td>21,120,880</td>
<td>2838</td>
<td>6360</td>
<td>44.6%</td>
<td>4.46</td>
<td>161.24</td>
</tr>
<tr>
<td>0.2</td>
<td>42,241,761</td>
<td>3858</td>
<td>6360</td>
<td>60.7%</td>
<td>3.03</td>
<td>109.60</td>
</tr>
<tr>
<td>0.5</td>
<td>105,604,404</td>
<td>5388</td>
<td>6360</td>
<td>84.7%</td>
<td>1.69</td>
<td>61.22</td>
</tr>
<tr>
<td>1</td>
<td>211,208,808</td>
<td>6360</td>
<td>6360</td>
<td>100.0%</td>
<td>1.00</td>
<td>36.13</td>
</tr>
</tbody>
</table>
## Validation
### All Patients

<table>
<thead>
<tr>
<th>Top Proportion</th>
<th>Total</th>
<th>Cases</th>
<th>Total Cases</th>
<th>Percent Cases</th>
<th>Ratio of Percent Cases to Expected Percent</th>
<th>Annualized Suicide Rate per 100,000 person-years</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0001</td>
<td>21,120</td>
<td>36</td>
<td>6360</td>
<td>0.6%</td>
<td>56.60</td>
<td>2045.45</td>
</tr>
<tr>
<td>0.0005</td>
<td>105,604</td>
<td>96</td>
<td>6360</td>
<td>1.5%</td>
<td>30.19</td>
<td>1090.87</td>
</tr>
<tr>
<td>0.001</td>
<td>211,208</td>
<td>190</td>
<td>6360</td>
<td>3.0%</td>
<td>29.87</td>
<td>1079.50</td>
</tr>
<tr>
<td>0.005</td>
<td>1,056,044</td>
<td>484</td>
<td>6360</td>
<td>7.6%</td>
<td>15.22</td>
<td>549.98</td>
</tr>
<tr>
<td>0.01</td>
<td>2,112,088</td>
<td>740</td>
<td>6360</td>
<td>11.6%</td>
<td>11.64</td>
<td>420.44</td>
</tr>
<tr>
<td>0.05</td>
<td>10,560,440</td>
<td>1796</td>
<td>6360</td>
<td>28.2%</td>
<td>5.65</td>
<td>204.08</td>
</tr>
<tr>
<td>0.1</td>
<td>21,120,880</td>
<td>2610</td>
<td>6360</td>
<td>41.0%</td>
<td>4.10</td>
<td>148.29</td>
</tr>
<tr>
<td>0.2</td>
<td>42,241,761</td>
<td>3650</td>
<td>6360</td>
<td>57.4%</td>
<td>2.87</td>
<td>103.69</td>
</tr>
<tr>
<td>0.5</td>
<td>105,604,404</td>
<td>5300</td>
<td>6360</td>
<td>83.3%</td>
<td>1.67</td>
<td>60.22</td>
</tr>
<tr>
<td>1</td>
<td>211,208,807</td>
<td>6360</td>
<td>6360</td>
<td>100.0%</td>
<td>1.00</td>
<td>36.13</td>
</tr>
</tbody>
</table>
## Prediction

### Suicide Risk Concentration

<table>
<thead>
<tr>
<th>1</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>145.6</td>
<td>74.2</td>
<td>38.5</td>
<td>31.9</td>
<td>23.5</td>
</tr>
<tr>
<td>68.0</td>
<td>44.5</td>
<td>30.8</td>
<td>25.5</td>
<td>23.5</td>
</tr>
<tr>
<td>43.7</td>
<td>29.7</td>
<td>21.2</td>
<td>17.9</td>
<td>16.9</td>
</tr>
<tr>
<td>14.6</td>
<td>12.6</td>
<td>11.3</td>
<td>10.7</td>
<td>10.1</td>
</tr>
<tr>
<td>10.2</td>
<td>9.1</td>
<td>8.8</td>
<td>8.0</td>
<td>8.1</td>
</tr>
<tr>
<td>4.8</td>
<td>4.6</td>
<td>5.0</td>
<td>4.8</td>
<td>4.8</td>
</tr>
<tr>
<td>3.8</td>
<td>3.7</td>
<td>3.7</td>
<td>3.6</td>
<td>3.5</td>
</tr>
<tr>
<td>2.6</td>
<td>2.7</td>
<td>2.7</td>
<td>2.6</td>
<td>2.6</td>
</tr>
<tr>
<td>1.7</td>
<td>1.7</td>
<td>1.6</td>
<td>1.6</td>
<td>1.6</td>
</tr>
<tr>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
</tbody>
</table>

### External Non-Suicide Death Risk Concentration

<table>
<thead>
<tr>
<th>1</th>
<th>3</th>
<th>6</th>
<th>9</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>-</td>
<td>-</td>
<td>8.2</td>
<td>10.9</td>
<td>8.0</td>
</tr>
<tr>
<td>12.3</td>
<td>9.7</td>
<td>9.3</td>
<td>10.2</td>
<td>9.1</td>
</tr>
<tr>
<td>9.2</td>
<td>10.3</td>
<td>10.1</td>
<td>10.0</td>
<td>8.7</td>
</tr>
<tr>
<td>7.1</td>
<td>7.1</td>
<td>6.8</td>
<td>6.3</td>
<td>5.9</td>
</tr>
<tr>
<td>5.7</td>
<td>5.4</td>
<td>5.5</td>
<td>5.0</td>
<td>4.7</td>
</tr>
<tr>
<td>3.4</td>
<td>3.3</td>
<td>3.1</td>
<td>3.0</td>
<td>2.9</td>
</tr>
<tr>
<td>2.7</td>
<td>2.6</td>
<td>2.6</td>
<td>2.5</td>
<td>2.5</td>
</tr>
<tr>
<td>2.2</td>
<td>2.0</td>
<td>2.0</td>
<td>2.0</td>
<td>1.9</td>
</tr>
<tr>
<td>1.5</td>
<td>1.4</td>
<td>1.4</td>
<td>1.4</td>
<td>1.4</td>
</tr>
<tr>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
</tbody>
</table>

External non-suicide mortality rates are about 3.5 * suicide rates.
Developing a practical suicide risk prediction model for targeting high-risk patients in the Veterans health Administration

Ronald C. Kessler\textsuperscript{1} | Irving Hwang\textsuperscript{1} | Claire A. Hoffmire\textsuperscript{2} | John F. McCarthy\textsuperscript{3} | Maria V. Petukhova\textsuperscript{4} | Anthony J. Rosellini\textsuperscript{4} | Nancy A. Sampson\textsuperscript{5} | Alexandra L. Schneider\textsuperscript{2} | Paul A. Bradley\textsuperscript{5} | Ira R. Katz\textsuperscript{6} | Caitlin Thompson\textsuperscript{7,8} | Robert M. Bossarte\textsuperscript{9,10}

\textsuperscript{1}Department of Health Care Policy, Harvard Medical School, Boston, Massachusetts, USA
\textsuperscript{2}VISN 19 Mental Illness Research, Education and Clinical Care Center, Denver, Colorado, USA
\textsuperscript{3}Office of Mental Health Operations, VA Center for Clinical Management Research, Serious Mental Illness Treatment Resource and Evaluation Center, Ann Arbor, Michigan, USA
\textsuperscript{4}Center for Anxiety and Related Disorders, Boston University, Boston, Massachusetts, USA
Goals

• To develop a limited model which achieves comparable, or better than the comprehensive proof of concept model

• Improve prediction & risk concentration
  – Improve model stability
  – Improve feasibility of real-time computation
    • Reduce the number of variables
      – Max = 350 + 31 interaction terms
    • Consider variable types and computation intensity

• Decrease processing requirements
Methods (Step 1)

• 3-Fold cross-validation
  – logistic regression (weighted) w/ forward selection
  – Sample
    • Begin with the prediction sample from the proof of concept publication - requires 2:200 (or 1:100) weighting to achieve population-level figures
    • 1,059,184 patient-month records for 980,889 individuals
    • 3,180 case records and 1,056,004 control records.
Methods (Step 1)

• **3-Fold cross-validation**
  
  – **Fold creation**
    
    • Systematic random sampling to assign each individual to one of three folds
      
      – All records for an individual were included in the same fold
      
      – For patients with both case and control records, fold was assigned based on the case record
      
      – For patients with multiple control records, the fold was assigned based on the most recent record
    
    • Variables used for systematic sampling:
      
      – Age
      
      – Sex
      
      – Residence (Urban/Rural/Missing)
      
      – Any psychiatric diagnosis in the past 24 months
      
      – Any suicide attempt in the past 12 months
    
    • \( n=326,963 \) individuals/fold, no significant differences in the number of records
Methods (Step 1)

• 3-Fold cross-validation
  – Two 25% analysis subsamples (A & B) were drawn
    • Each contains cases and a mutually exclusive 25% sample of controls
    • The cross-validation macro first run without restricting the number of variables included in the final model to determine and upper threshold
    • Total of 350 possible variables
      – all variables used in the predictive model from the McCarthy et al, 2015 paper except the 31 interaction terms
    • Macro run restricting the number variables to 10, and increasing the number of variables allowed into the model by 10 until the upper threshold was reached.
    • Weighted to population level (1:400)
Methods (Step 1)

• 3-Fold cross-validation
  – Output Measures
    • AUC
      – Area under the ROC curve
    • Risk Concentration
      – Proportion of observed suicides in each risk group/percentile/ventile).
      – Percentiles or ventiles are created by sorting the sample population by the predicted suicide risk score and selecting cut points to equally divide the sample into the appropriate number of equally sized groups.
  • Suicide rate computation within risk percentiles per 100,000 person-years
Conclusions From Model Revisions

• ~60 variables can be used to model suicide risk as efficiently as achieved in with the full proof of concept model

• R glmnet and penalized elastic net models used to choose predictors
  – Ease of real-time variable computation should be considered
    • Could also be considered prior to optimizing model to reduce variable pool
Questions

• Does the use of advanced analytics, including machine learning, represent a paradigm shift?
  – Will models such as these move our field forward?
• What next?
  – Should we be starting with the end?
• What should we expect to happen if we are successful?
  – What can we hope to achieve?