Real-time stats for real-time problems

The development of a risk tool to predict and prevent psychiatric crises in Multnomah County, Oregon

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Background

- Multnomah County--most of Portland, a few of the suburbs
- Mental Health & Addiction Services Division (MHASD)
  - Direct services
  - 24/7 crisis line
  - Care coordination and outreach
  - Management of Medicaid behavioral health benefit for county Medicaid members (Oregon is an ACA expansion state)
    - Not just authorizing treatment and paying claims--partnering with community providers and CCO to improve care, improve access, further behavioral/physical healthcare integration, increase system capacity, monitor outcomes, etc.; invested in the health of the system as a whole
Background

- Acute care--inpatient psychiatric hospitalizations, behavioral health-driven ER visits, psychiatric emergency services
  - Want to reduce acute care utilization by engaging clients in different levels of care that sustainably address their needs
- We follow up on hospitalizations and ED visits...but what if we could get there before they happened?
- Predictive risk modeling*
  - Uses standard statistical analyses of past events to help predict future ones reliably

*Many thanks to the Oregon Criminal Justice Commission for giving us the “behind the scenes” details of their predictive risk tool; many of our methodology decisions were informed by their work.
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Preparation & process

● Our events:
  ○ Acute care event
    ■ Inpatient psychiatric hospitalizations
    ■ Psychiatric emergency services (PES)
    ■ Emergency department visits attributable to mental health and/or substance use diagnoses

● Our sample:
  ○ HSO members with 1+ year coverage & SPMI

● Our time period:
  ○ January 1, 2015 to June 30, 2017 (2.5 years)

Result: 13,158 clients; 11,222 acute care events
Preparation & process

- Our data sources:
  - Healthcare claims
  - Call center records
  - Medicaid enrollment data

- Variables to explore:
  - Met with front-line mental health staff for input on what they perceived as contributing factors and/or indicators* of impending crisis, common traits of high utilizers, etc.

*An indicator doesn’t have to cause the event, but can be a warning sign; e.g., multiple calls to the crisis line before a hospitalization
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Analysis

- Multiple-failure Cox survival analysis (Stata’s stcox)
  - Better suited to data structure
    - Didn’t want to lose data on multiple events by one person; accounts for different lengths of observation time, acknowledges that acute care event can happen after observation period ends

- Logistic regression (Stata’s logit, vce(cluster id), and lroc)
  - More easily interpreted in terms of predictive fit (use of area under ROC curve); more familiar; can still adjust for multiple events by individuals

- Comparing the models
  - Output/models very similar
  - Decided to use logistic to proceed
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Analysis

- Significant non-demographic variables (odds ratio):
  - No recent mental health outpatient history (4.5)
  - Multiple SPMI-level diagnoses (4.3)
  - History of substance use (2.9)
  - Week with 2+ crisis line calls (2.9)
  - History of homelessness/housing instability (1.7)
  - Receiving SSI for disability (1.7)
  - Healthcare encounters with respiratory (1.6) or pain issues (1.5) as primary diagnosis

- Area under the ROC curve: 0.85
  - 0.9 to 1 considered excellent; 0.8 to 0.89 → very good
Validating results

● #1: Equity
  ○ Avoid systematically under/over-predicting for any population
    ■ Ran model without demographics included, on each individual race, age, sex, language, as well as random combinations
    ○ Intent: ensure it works well for different populations
      ○ Short answer: yes, it does!

● #2: Different, but similar, sample
  ○ Run the exact same models with all SPMI members with under 1 year of coverage (pop. of 3,380)
    ■ ORs virtually the same, ROC of 0.84; important because we often work with incomplete data → realistic scenario
    ○ Good sign to proceed!

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Condensing complex information into something easily interpreted and actionable: how do we get from A to B?

High risk clients for outreach, 10/31/2018

Jack Jones  Risk score: 10
Diane Dayton  Risk score: 8
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#### Hypothetical client: “Harry Potter”

<table>
<thead>
<tr>
<th>Risk Factor</th>
<th>Response</th>
<th>Odds ratio</th>
<th>Subtotal</th>
</tr>
</thead>
<tbody>
<tr>
<td>No recent mental health outpatient history (last 120 days)?</td>
<td>Yes (1)</td>
<td>4.518399</td>
<td>4.518399</td>
</tr>
<tr>
<td>Multiple SPMI diagnoses (last 12 months)?</td>
<td>No (0)</td>
<td>4.334528</td>
<td>0</td>
</tr>
<tr>
<td>Substance use history (last 12 months)?</td>
<td>Yes (1)</td>
<td>2.928598</td>
<td>2.928598</td>
</tr>
<tr>
<td>Week with 2+ crisis line calls (last 3 weeks)?</td>
<td>Yes (1)</td>
<td>2.892232</td>
<td>2.892232</td>
</tr>
<tr>
<td>SSI for disability (any time)?</td>
<td>No (0)</td>
<td>1.696737</td>
<td>0</td>
</tr>
<tr>
<td>History of housing instability (any time)?</td>
<td>Yes (1)</td>
<td>1.687269</td>
<td>1.687269</td>
</tr>
<tr>
<td>Primary respiratory complaint at healthcare visit (last year)?</td>
<td>No (0)</td>
<td>1.606196</td>
<td>0</td>
</tr>
<tr>
<td>Primary pain complaint at healthcare visit (last year)?</td>
<td>No (0)</td>
<td>1.546471</td>
<td>0</td>
</tr>
<tr>
<td>Constant term</td>
<td>1</td>
<td>0.0372867</td>
<td>0.0372867</td>
</tr>
</tbody>
</table>

**Subtotal** = 12.0637847

Scaling to range of 0 to 10

**Final score** = 6
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Percent of cases experiencing acute care events, by risk score

- 0: 5.0%
- 1: 10.2%
- 2: 18.3%
- 3: 29.2%
- 4: 46.3%
- 5: 62.2%
- 6: 76.9%
- 7: 86.1%
- 8: 90.9%
- 9: 93.9%
- 10: 95.6%
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Building the tool

- We have a score--now how do we use it?
  - Automated stored SQL procedure; updated every 24 hours
  - Information available to staff via a Tableau dashboard
    - Look up specific members individually, view all members enrolled in a certain type of services, view members by risk level (e.g., list of all of today's high risk members), explore population averages for different demographics or types of services…
  - Clarity on ethics
    - Only proactively offering help/services, not denying; respecting client autonomy; not intended to override clinical judgment
    - Human behavior too nuanced, messy to reduce to a single number; only intended as an additional data point to help inform
Acute Care Risk

Total Clients: 109,391
Avg. Risk Score: 2.31

Clients per Risk Score:
- 0: 1,377
- 1: 3,851
- 2: 68,002
- 3: 22,221
- 4: 10,275
- 5: 294
- 6: 31
- 7: 10
- 8: 1

Risk Group:
- Low Risk: 75,950
- Medium-Low Risk: 32,496
- Medium-High Risk: 924
- High Risk: 11

Gender:
- Female: 69,735
- Male: 50,618

Race:
- AFRICAN-AMERICAN: 9,452
- ASIAN: 6,054
- CAUCASIAN: 46,847
- HISPANIC: 4,820
- NATIVE AMERICAN: 966
- OTHER: 38,881
- PACIFIC ISLANDER: 391
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### Acute Care Risk

<table>
<thead>
<tr>
<th>Policy Id</th>
<th>Full Name</th>
<th>Score</th>
<th>Phone</th>
<th>Gender</th>
<th>Race</th>
<th>Age Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABC123</td>
<td>LEIA ORGANA SOLO</td>
<td>5</td>
<td>123-456-7890</td>
<td>Female</td>
<td>WHITE</td>
<td>50+</td>
</tr>
<tr>
<td>DEF456</td>
<td>TYRION LANNISTER</td>
<td>7</td>
<td>234-567-8901</td>
<td>Male</td>
<td>OTHER</td>
<td>30-39</td>
</tr>
<tr>
<td>GHI789</td>
<td>HERMIONE GRANGER</td>
<td>5</td>
<td>345-678-9012</td>
<td>Female</td>
<td>AFRICAN-AMERICAN</td>
<td>18-29</td>
</tr>
<tr>
<td>JKL012</td>
<td>ARAGORN S O ARATHO</td>
<td>6</td>
<td>456-789-0123</td>
<td>Female</td>
<td>WHITE</td>
<td>50+</td>
</tr>
<tr>
<td>MNO345</td>
<td>KVOTHE ARLIDENSON</td>
<td>7</td>
<td>Null</td>
<td>Male</td>
<td>OTHER</td>
<td>18-29</td>
</tr>
<tr>
<td>PQR678</td>
<td>SHURI</td>
<td>5</td>
<td>567-890-1234</td>
<td>Female</td>
<td>AFRICAN-AMERICAN</td>
<td>Under 18</td>
</tr>
<tr>
<td>STU901</td>
<td>RA S AL GHUL</td>
<td>7</td>
<td>678-901-2345</td>
<td>Male</td>
<td>ASIAN</td>
<td>40-49</td>
</tr>
</tbody>
</table>

### Referral Details

<table>
<thead>
<tr>
<th>Authorization Type</th>
<th>Referral Id</th>
<th>Vendor Nm</th>
<th>Elig Eff Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>GLOBAL - Level B Adult Global - Primary A... RESIST999</td>
<td>Lifewoks Northwest</td>
<td>1/1/2014</td>
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<tr>
<td>Outpatient SUD 1/1/17 - Medication Assi... WESTER999</td>
<td>CODA CD</td>
<td>2/15/2014</td>
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<tr>
<td>Null</td>
<td>Null</td>
<td>Null</td>
<td>3/31/2015</td>
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<tr>
<td>Null</td>
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<td>Null</td>
<td>4/1/2015</td>
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<td>Null</td>
<td>Null</td>
<td>Null</td>
<td>5/15/2016</td>
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<tr>
<td>Null</td>
<td>Null</td>
<td>Null</td>
<td>6/30/2016</td>
</tr>
<tr>
<td>Exceptional Needs - Supported Employm... GOTHAM999</td>
<td>Cascadia Behavioral Health</td>
<td>7/1/2017</td>
<td></td>
</tr>
</tbody>
</table>
Going “live” with entire population

- One more test: how will this work in the “real world”?
  - If someone used the score today, how accurate would it be?
    - Track actual events for next 30 days; use score as main predictor
    - Predictive power fell to 0.77 → still acceptable, but not as good

- Up to present day; implementation phase

Percent experiencing acute care event, by score range

- Low risk (0 to 2)
- Medium-low risk (3 to 4)
- Medium-high risk (5 to 7)
- High risk (8 to 10)

SPMI (original sample)  All HSO (PIT: 5/15/18, viewed through 9/10/18, minus children)
Many thanks to...

- Devarshi Bajpai, Medicaid program manager;
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- Leticia Sainz, call center supervisor;
- Kelly Officer, of the Oregon Criminal Justice Commission.