Strategies to Achieve Alignment, Collaboration, and Synergy across Delivery and Financing Systems

Using Predictive Modeling to Identify Patients Who Need Social Services

Research In Progress Webinar
Wednesday, January 10, 2017
12:00-1:00 pm ET/ 9:00 am-10:00 pm PT

Funded by the Robert Wood Johnson Foundation
Agenda

Welcome:  CB Mamaril, PhD
Research Faculty, RWJF Systems for Action National Coordinating Center, University of Kentucky College of Public Health

Presenter:  Joshua R. Vest, PhD, MPH
Director, Center for Health Policy
Associate Professor, Health Policy & Management
Indiana University Richard M. Fairbanks School of Public Health at IUPUI
joshvest@iu.edu

Commentary Speaker:
Michael Shafer, PhD
Director
Center for Applied Behavioral Health Policy
Professor
Arizona State University
michael.shafer@asu.edu

Questions and Discussion:  Moderated by Dr. Mamaril
Presenter

Joshua R. Vest, PhD, MPH
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### Upcoming

<table>
<thead>
<tr>
<th>Date</th>
<th>Time</th>
<th>Title</th>
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<tbody>
<tr>
<td>Wednesday, January 24</td>
<td>12-1pm ET/ 9-10am PT</td>
<td><strong>Optimizing Governmental Health and Social Spending Interactions</strong></td>
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<td></td>
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<td>Johns Hopkins University Bloomberg School of Public Health</td>
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<td></td>
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<td>Principal Investigators: Beth Resnick, DrPH, MPH, and David Bishai, MD, MPH, PhD</td>
</tr>
<tr>
<td>Wednesday, February 7</td>
<td>12-1pm ET/ 9-10am PT</td>
<td><strong>Strengthening the Carrying Capacity of Local Health and Social Service Networks</strong></td>
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<td>Trailhead Institute in Colorado</td>
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<td>Principal Investigators: Danielle Varda, PhD, and Katie Edwards, MPA</td>
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<tr>
<td>Wednesday, February 21</td>
<td>12-1pm ET/ 9-10am PT</td>
<td><strong>Linking Medical Homes to Social Service Systems for Medicaid Populations</strong></td>
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<td>National Committee for Quality Assurance</td>
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<tr>
<td></td>
<td></td>
<td>Principal Investigators: Sarah Scholle, DrPH, and Keri Christensen, MS</td>
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</tbody>
</table>
Thank you for participating in today’s webinar!

For more information about the webinars, contact: SystemsforAction@uky.edu
111 Washington Avenue #201, Lexington, KY 40536
859.218.2289
www.systemsforaction.org
Speaker Bios

Joshua R. Vest, PhD, MPH, is a health services researcher with interests in organizational determinants and effectiveness of health information technology and systems, specifically the adoption, utilization, and policy issues of technologies that facilitate the sharing of patient information between different organizations. He is widely published and his work has employed a variety of research techniques from large scale database analyses, to geographical information system mapping, to survey research, to qualitative focus groups and interviews. As a former local public health practitioner, Dr. Vest has a particular interest in effective public health information systems including the role of information technology governance structures on local public health departments' adoption of information technology and systems, the structure of state and local public health information systems, as well as an evaluation of email intervention to improve disease notification efforts.

Michael S. Shafer, Ph.D., is a professor in the School of Social Work at Arizona State University’s College of Public Service and Community Solutions where he also holds affiliate appointments in the Center for Health Information Research and the School of Criminology and Criminal Justice. Dr. Shafer is the founding director of the Center for Applied Behavioral Health Policy which has, for the past 25 years, conducted cutting edge research on the adoption and implementation of innovative practices in behavioral health care. Dr. Shafer has authored more than 40 peer-reviewed research articles and generated more than $45 million in grants and contracts that target capacity building and innovation in behavioral health services. Dr. Shafer earned his Ph.D. in Education in 1988 from Virginia Commonwealth University. He has received numerous awards and citations, including recognition from the U.S. Department of Justice for the development of crisis intervention training for law enforcement personnel. Dr. Shafer is a frequent contributor to professional literature and he consults with behavioral health agencies throughout the country.
Using predictive modeling to identify patients who need social services

Joshua R Vest, PhD, MPH
Director, Center for Health Policy
Associate Professor, Health Policy & Management
Indiana University Richard M Fairbanks School of Public Health at IUPUI
Affiliated Scientist, Regenstrief Institute, Inc.

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Acknowledgements

Indiana University
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• Jennifer Williams
• Karen Comer

Eskenazi Health
• Dawn Haut
• Jennifer Ferrell


• Donna Burke
• Alisha Jessup
Predictive modeling in health care: statistical approaches to identifying patients at high risk (more likely) for negative outcomes
Predictive modeling is widely applied...
Limitations of current predictive modeling

- Limited to EHR or claims data
- Social determinants often absent
- Often single-site data

- Focus on “too late” outcomes (reactive not proactive)
- Don’t provide insights into what services patients should get
Objective 1: Evaluate predictive models that use combinations of clinical, socioeconomic, and public health data

Environmental & social context

Neighborhood health context

Diagnosis & Utilization

Algorithm

Health Behaviors & System-wide health data
Diagnosis & Utilization

Environmental & social context

Data on health status

Neighborhood health context

Algorithm

Health Behaviors & System-wide health data
Diagnosis & Utilization

Environmental & social context

Neighborhood health context

Data on drivers of health

Algorithm

Health Behaviors & System-wide health data
Environmental & social context

Neighborhood health context

A comprehensive patient view

Diagnosis & Utilization

Algorithm

Health Behaviors & System-wide health data
Framework for organizing the factors included in risk identification tool

The only data included in most prediction models

Economic & social opportunities & resources

Living & working conditions in homes & communities

Medical care

Personal behavior

HEALTH


What we are adding
Objective 2: Contribution of these data on the novel outcome of referrals to social services
To be responsive to new payment strategies, health care organizations in the US are beginning to offer these non-medical services.
Objective 1:
Evaluate predictive models that use combinations of clinical, socioeconomic, and public health data.

Objective 2:
Contribution of these data on the novel outcome of referrals to social services.
Approach

Compare the performance of risk prediction models with:

1) clinical data only

2) clinical data with community-level socioeconomic & public health indicators
Setting & sample

- Eskenazi Health outpatient clinics
  - Indianapolis safety-net provider (for medical indigent)
  - urban population
  - all social services offered on a co-located basis (no referrals to other organizations)
- 84,317 adult patients
  - at least 1 outpatient visit between 2011-2016

Sample demographics

<table>
<thead>
<tr>
<th>Demographics</th>
<th>Sample demographics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (mean, sd)</td>
<td>43.9 (15.6)</td>
</tr>
<tr>
<td>Male gender</td>
<td>35.1</td>
</tr>
<tr>
<td>Race / ethnicity</td>
<td></td>
</tr>
<tr>
<td>White, non-Hispanic</td>
<td>25.2</td>
</tr>
<tr>
<td>African American, non-Hispanic</td>
<td>37.2</td>
</tr>
<tr>
<td>Hispanic</td>
<td>19.5</td>
</tr>
<tr>
<td>Diagnoses</td>
<td></td>
</tr>
<tr>
<td>Hypertension</td>
<td>38.7</td>
</tr>
<tr>
<td>Asthma</td>
<td>7.9</td>
</tr>
<tr>
<td>Cancer</td>
<td>7.6</td>
</tr>
<tr>
<td>COPD</td>
<td>9.5</td>
</tr>
<tr>
<td>Depression</td>
<td>19.0</td>
</tr>
<tr>
<td>Diabetes</td>
<td>20.3</td>
</tr>
<tr>
<td>Substance abuse</td>
<td>15.1</td>
</tr>
<tr>
<td>Tobacco use</td>
<td>21.3</td>
</tr>
</tbody>
</table>
Data & measures (outcome)

Referral to social services
- Social work
- Dietitian
- Mental health
- All other services (due to low frequency)

Data sources
- Eskenazi EHR billing and encounter data
- scheduling system data (including kept, missed, & cancelled appointments)
- unstructured EHR orders and notes
Data & measures (predictors)

Data & measures (predictors)

- Diagnoses
  - Asthma
  - Coronary artery disease
  - Chronic kidney disease
  - Congestive heart failure
  - COPD
  - Stroke / cerebrovascular accident
  - Depression
  - Diabetes
  - Hypertension
  - Ischemic vascular disease
  - Obesity
  - Pregnancy
  - ….

- ED visits (number)
- Inpatient admissions
- PCP visits
- Mental illness

- Smoking
- Substance abuse

• **Indiana Network for Patient Care**

• US’ oldest HIE
  - Started at Regenstrief Institute in 1995

• One of the nation’s largest
  - > 80 hospitals’ medical records
  - 17.2 million individual patients
  - 4.6 billion clinical observations
  - 165 million text reports
  - Over 68% of Indiana population captured in 2014

• Data include:
  - admission and discharge
  - lab reports
  - Microbiology
  - Pathology
  - Radiology
  - Cardiology
  - EKG data
Data & measures (predictors)

- Smoking prevalence
- Perceived safety
- Mortality rates
- Infant mortality rates
- Maternal smoking
- Overweight / obesity prevalence
- Walkability

Framework for organizing the factors

### Social Determinants of Health

<table>
<thead>
<tr>
<th>Economic Stability</th>
<th>Neighborhood and Physical Environment</th>
<th>Education</th>
<th>Food</th>
<th>Community and Social Context</th>
<th>Health Care System</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment</td>
<td>Housing</td>
<td>Literacy</td>
<td>Hunger</td>
<td>Social integration</td>
<td>Health coverage</td>
</tr>
<tr>
<td>Income</td>
<td>Transportation</td>
<td>Language</td>
<td>Access to healthy options</td>
<td>Support systems</td>
<td>Provider availability</td>
</tr>
<tr>
<td>Expenses</td>
<td>Safety</td>
<td>Early childhood education</td>
<td></td>
<td>Community engagement</td>
<td>Provider linguistic and cultural competency</td>
</tr>
<tr>
<td>Debt</td>
<td>Parks</td>
<td>Vocational training</td>
<td></td>
<td>Discrimination</td>
<td>Quality of care</td>
</tr>
<tr>
<td>Medical bills</td>
<td>Playgrounds</td>
<td>Higher education</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Support</td>
<td>Walkability</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Health Outcomes**
- Mortality, Morbidity, Life Expectancy
- Health Care Expenditures
- Health Status
- Functional Limitations

Analytic approach: performance of prediction models with novel data

1) Clinical data only (41 variables)
2) Clinical plus socioeconomic & public health (48 variables)
Prevalence of social service referral need

<table>
<thead>
<tr>
<th>Type of service</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Any service</td>
<td>53.0</td>
</tr>
<tr>
<td>Mental health</td>
<td>18.5</td>
</tr>
<tr>
<td>Social work</td>
<td>8.7</td>
</tr>
<tr>
<td>Dietitian</td>
<td>32.6</td>
</tr>
<tr>
<td>Other services</td>
<td>20.0</td>
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</table>
Prediction for social services referrals was in the “useful” range.

Area under the ROC curve values for each decision model

<table>
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<tr>
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<th>Clinical data</th>
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<tbody>
<tr>
<td>Any referral</td>
<td>0.745</td>
</tr>
<tr>
<td>Mental health</td>
<td>0.785</td>
</tr>
<tr>
<td>Social work</td>
<td>0.731</td>
</tr>
<tr>
<td>Dietitian</td>
<td>0.743</td>
</tr>
<tr>
<td>Other referral</td>
<td>0.711</td>
</tr>
</tbody>
</table>

Consistent with performance of models on:
• Mortality
• Readmissions
• Disease development
• Care coordination need
Socioeconomic & public health data did not contribute significantly.

Area under the ROC curve values for each decision model

<table>
<thead>
<tr>
<th></th>
<th>Clinical data</th>
<th>Clinical + socioeconomic &amp; public health</th>
</tr>
</thead>
<tbody>
<tr>
<td>Any referral</td>
<td>0.745</td>
<td>0.741</td>
</tr>
<tr>
<td>Mental health</td>
<td>0.785</td>
<td>0.778</td>
</tr>
<tr>
<td>Social work</td>
<td>0.731</td>
<td>0.714</td>
</tr>
<tr>
<td>Dietitian</td>
<td>0.743</td>
<td>0.730</td>
</tr>
<tr>
<td>Other referral</td>
<td>0.711</td>
<td>0.708</td>
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</table>
Socioeconomic & public health data did not contribute significantly.
Limitations

• Socioeconomic measures at aggregate level
  – small geographic area, but still aggregate
  – limited geographic variation because only within a single urban area
  – individual level measures generally unavailable from EHRs

• High need, vulnerable population
  – limited generalizability
  – probably lots of unmet need

• All services were co-located with primary care
  – May not apply to referrals to outside services / other organizations

• No assessment whether or not the referral was appropriate or appointment was kept
Predictive models for referrals to social services are currently live. Before clinics open

<table>
<thead>
<tr>
<th>MRN</th>
<th>Name</th>
<th>Provider</th>
<th>DOB</th>
<th>Any referral need category</th>
<th>Mental health need category</th>
<th>Any referral probability</th>
<th>Mental health probability</th>
<th>Dietitian need category</th>
<th>Social Work need category</th>
<th>Social Work probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>Low risk</td>
<td>Rising risk</td>
<td>0.70</td>
<td>Rising risk</td>
<td>0.50</td>
<td>Low risk</td>
<td>Rising risk</td>
</tr>
<tr>
<td>2</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>Low risk</td>
<td>Rising risk</td>
<td>0.60</td>
<td>Rising risk</td>
<td>0.40</td>
<td>Low risk</td>
<td>Rising risk</td>
</tr>
<tr>
<td>3</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>Rising risk</td>
<td>Low risk</td>
<td>0.90</td>
<td>Low risk</td>
<td>0.20</td>
<td>Low risk</td>
<td>Rising risk</td>
</tr>
<tr>
<td>4</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>Low risk</td>
<td>Low risk</td>
<td>0.60</td>
<td>Low risk</td>
<td>0.20</td>
<td>Low risk</td>
<td>Rising risk</td>
</tr>
<tr>
<td>5</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>Low risk</td>
<td>Low risk</td>
<td>0.50</td>
<td>Low risk</td>
<td>0.20</td>
<td>Low risk</td>
<td>Low risk</td>
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<tr>
<td>6</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>Rising risk</td>
<td>Low risk</td>
<td>0.90</td>
<td>Low risk</td>
<td>0.20</td>
<td>Low risk</td>
<td>High risk</td>
</tr>
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<td>7</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>Low risk</td>
<td>Low risk</td>
<td>0.90</td>
<td>High risk</td>
<td>0.20</td>
<td>Low risk</td>
<td>Low risk</td>
</tr>
<tr>
<td>8</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>Low risk</td>
<td>Low risk</td>
<td>0.50</td>
<td>Low risk</td>
<td>0.20</td>
<td>Low risk</td>
<td>Low risk</td>
</tr>
<tr>
<td>9</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>Low risk</td>
<td>Low risk</td>
<td>0.40</td>
<td>Rising risk</td>
<td>0.67</td>
<td>Low risk</td>
<td>Rising risk</td>
</tr>
<tr>
<td>10</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>Low risk</td>
<td>Rising risk</td>
<td>0.40</td>
<td>Rising risk</td>
<td>0.50</td>
<td>Rising risk</td>
<td>Rising risk</td>
</tr>
</tbody>
</table>

The predicted probably the patient is in need of mental health services.
Impact of predicted models on referral rates currently being evaluated.

- 3 clinic locations live
- Next 3 clinic locations live
- Last 3 clinic locations live

<table>
<thead>
<tr>
<th>June</th>
<th>July</th>
<th>August</th>
<th>September</th>
<th>October</th>
<th>November</th>
<th>December</th>
<th>January</th>
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</thead>
</table>

Baseline
Using predictive modeling to identify patients who need social services.

• Indications that predictive modeling for social services may be useful
  – models leveraged EHR and HIE data
  – performance could be improved, but consistent with literature

• Socioeconomic & public health measures (at the aggregate level) did not improve model performance