NIH Collaboratory Grand Rounds

*Improving Chronic Disease Management with Pieces: Overview of PCCI and Pieces™*

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Friday, January 16, 2015  
12:00-1:00 pm CT
Objectives

- What is electronic health predictive analysis (e-HPA)?
- PCCI’s work in this area: Pieces™ software
- Application of Pieces™ in the CKD Pilot Study and ICD-Pieces trial
- Pieces™ in Community Health Information Exchanges
1. What does this patient have?
2. What will this patient develop?
3. What will be the effect of a given therapy?
Prediction in the Context of Modern Medicine

Doubling Time of Medical Knowledge

Year

1900: 150 years
Prediction in the Context of Modern Medicine

The graph illustrates the doubling time of medical knowledge from 1900 to 2100. The timeline shows a significant decrease in doubling time, indicating rapid advancements. It is noted that we are currently at 1 year, indicating a rapid pace of knowledge doubling in recent years.
Prediction in the Context of Modern Medicine

- Staggering increase in medical information
- Increasing volume of decisions at multiple levels
- High fragmentation of care
- Increasing capacity for error
Some Definitions

**Clinical risk prediction models:** defined as models that “combine a number of characteristics (e.g. related to the patient the disease or treatment) to predict a diagnostic or prognostic outcome” [Steyerberg 2009]

**Electronic health care predictive analytics (e-HPA):** the technologies or software systems that can autonomously employ – and sometimes re-engineer, modify, or update – these models” [Amarasingham 2014]
PCCI Organizational Background

A 501c(3) non-profit research and development corporation specializing in the development of clinical prediction and surveillance software to help prevent adverse clinical events.
PCCI Scientific Funding for Predictive Modeling
Every Adverse Event has a Timeline

- **Hours**
  - Cardio-Pulmonary Arrest
  - Sepsis

- **30 days**
  - Readmissions

- **90 days**
  - Asthma Complications
  - Short-Term Diabetic Complications

- **Years**
  - Preventable Hospitalizations
  - Triad: diabetes, hypertension, CKD
Every Adverse Event has a Timeline

Admission  24 hours  Discharge  30 Days  90 Days
Preventing Heart Failure Readmissions

- Admission
  - ID
  - Risk
  - List
  - Orders
  - 24 hours
  - Inpatient Intervention

- Discharge
  - 7 days
  - Outpatient Intervention

- 30 Days

- 90 Days
  - Evaluation & Improvement

- EMR

Pieces
Identification of HF patients in Real-Time Using Natural Language Processing and Data Mining
“68 yo WF presents with acute on chronic non ischemic systolic and diastolic chf, severely depressed ef and grade ii diastolic dysfunction.”

<table>
<thead>
<tr>
<th>Disease/ Symptom</th>
<th>Time</th>
<th>Attribute</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acute Heart Failure</td>
<td>current and primary</td>
<td>• Systolic, significant depression in ejection fraction;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Diastolic dysfunction, grade 2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Non-ischemic</td>
</tr>
<tr>
<td>Chronic Heart Failure</td>
<td>historic</td>
<td></td>
</tr>
</tbody>
</table>
System calculates risk for readmission
Identifying High-Risk Patients in Real-Time

Amarasingham et al, Medical Care, 2010
Pieces provides list of targeted high risk patients
Activation of Clinical Pathways in the EMR

- Admission: ID, Risk, List, Orders
- Discharge: Inpatient Intervention
- 30 Days: Outpatient Intervention
- 90 Days: Evaluation & Improvement

Pieces

EMR
Pieces tracks interventions in the EMR
Pieces monitors outcomes
Complexities of Predictive Modeling in Healthcare

ABSTRACT Predictive analytics, or the use of electronic algorithms to forecast future events in real time, makes it possible to harness the power of healthcare data to improve patient care. This approach can help identify patients at risk for adverse events, leading to earlier intervention and improved outcomes. However, predictive modeling also raises ethical concerns, including the potential for discrimination and the need for transparency in decision-making processes. This paper explores the legal and ethical implications of implementing predictive analytics in healthcare settings.

By I. Glenn Cohen, Ruben Amarasingham, Anand Shah, Bin Xie, and Bernard Lo

ABSTRACT The use of predictive modeling for real-time clinical decision making is increasingly recognized as a way to achieve the Triple Aim of improving outcomes, enhancing patients' experiences, and reducing health care costs. The development and validation of predictive models...

By Ruben Amarasingham, Rachel E. Patzer, Marco Huesch, Nam Q. Nguyen, and Bin Xie

Implementing Electronic Health Care Predictive Analytics: Considerations And Challenges
The Complexities of Predictive Modeling

1. Interventions for highest risk patients *
2. Considering clinical vs. social risk
3. Explanation vs. Prediction
4. Non-health care data sources *
5. Changing EMR data models
6. Changing clinical interventions
7. Changing populations

Amarasingham et al, Health Affairs, 2014
Concentrated care management efforts on ¼ of the patients

26% relative reduction in odds of readmission

Absolute reduction of 5 readmissions per 100 index admissions

Amarasingham et al, BMJ, 2013
A Different Hospital: Readmission Performance

The graph illustrates the readmission rate percentages from 2011-2012 to 2014-2015. Before the intervention (Pre-Intervention), the readmission rate was high, reaching 21.43% in 2012. After the intervention (Post-Intervention), the rate dropped significantly to 13.29% in 2014. The graph shows a consistent decline in the readmission rate post-intervention, indicating improved performance.
## NIH-Funded CKD Pilot Study

<table>
<thead>
<tr>
<th>Clinical Measurement</th>
<th>Screening % at Goal</th>
<th>Last follow-up visit % at Goal</th>
<th>P-value (McNemar’s test)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Follow-up duration, month</td>
<td>11.2 [0.2 – 21.5]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Systolic blood pressure</td>
<td>34.6%</td>
<td>44.0%</td>
<td>0.14</td>
</tr>
<tr>
<td>Diastolic blood pressure</td>
<td>57.9%</td>
<td>66.1%</td>
<td>0.17</td>
</tr>
<tr>
<td>ACEI/ARB</td>
<td>57.8%</td>
<td>87.2</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Statin</td>
<td>45.0%</td>
<td>79.8</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

*if positive test for proteinuria or albuminuria, then goal BP <130/80; Otherwise goal BP < 140/90.*
ICD-Pieces Study Sites
Connecting the Community: WW Caruth

Pieces Plexus™

First Responders

400+ Community-Based Service Organizations

Healthcare Organizations via regional HIE

Dallas County Jail
Connecting the Community: WW Caruth

- Leverages predictive and prescriptive analytics on medical and social data to identify at risk individuals
Thank You!
Questions

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www.pccipieces.org