
May 2016
connecting researchers to create new possibilities

edmforum
knowledge inspiring health
Learning Health System According to Chuck Friedman

The LHS is Bigger than BD2K: It Must Do This

Not This
Learning Health System According to ONC
A Study Of The Impact Of Meaningful Use Clinical Quality Measures

Technology Challenges
The eCQM tools from vendors did not work as expected, and could not efficiently generate accurate measure results:

- Hospitals experienced significant difficulty implementing eCQM tools in their EHRs.
- The EHR could not draw relevant data from other systems.

Clinical Challenges
- eCQM reporting tools were poorly aligned with clinical workflow, necessitating the redesign of the patient care systems or the re-tooling of the reporting tools.
- Validation efforts were extensive, but not successful.
- Clinical staff did not trust the data.
- Rigid regulatory requirements caused the eCQMs to be out-of-date and out of step with advances in care; updates were available late in the process but were difficult to find and optional for vendors to incorporate.
Learning Health System According to ONC standards ≠ standardization
Where are standards for HIT and Clinical Research Harmonized?
pSCANNER Network
Connecting 21M patients’ EHR Data

- 5 University of California Medical Centers
- Cedar’s Sinai Hospital
- Pacific NW Rural Health Practice-Based Research Network
- Los Angeles Department of Health Services
- 5 multi-site FQHCs
- Children’s Hospital of Los Angeles
- Keck Medicine of USC
Interpreting Results in Context

- eCQM reporting tools were poorly **aligned with clinical workflow**, necessitating the redesign of the patient care systems or the **re-tooling of the reporting tools**.
- **Validation** efforts were extensive, but not successful.
- Clinical staff did not **trust the data**.
- Rigid regulatory requirements caused the eCQMs to be out-of-date and out of step with advances in care; updates were available late in the process but were difficult to find and optional for vendors to incorporate.
Reverse Engineering Measures of Clinical Care Quality: Sequential Pattern Mining

Hsuan Chiu\textsuperscript{1(✉)} and Daniella Meeker\textsuperscript{2}

\textsuperscript{1} Department of Computer Science, University of California, Los Angeles, USA  
cherylautumn@cs.ucla.edu

\textsuperscript{2} Department of Preventive Medicine, University of Southern California, Los Angeles, USA

<table>
<thead>
<tr>
<th>PtnN</th>
<th>DDI</th>
<th>Coef</th>
<th>adjP</th>
<th>Drug sequence</th>
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<tr>
<td>48</td>
<td>Moderate</td>
<td>0.353</td>
<td>0.001</td>
<td>Furosemide → Albuterol</td>
</tr>
<tr>
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<td>0.450</td>
<td>0.000</td>
<td>salmeterol fluticasone</td>
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<tr>
<td>132</td>
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<td>0.343</td>
<td>0.049</td>
<td>Azithromycin → Prednisone</td>
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<tr>
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<td>0.044</td>
<td>Acetaminophen → Warfarin</td>
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<tr>
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<td>0.041</td>
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<tr>
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<tr>
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<tr>
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<tr>
<td>96</td>
<td>Moderate</td>
<td>0.228</td>
<td>0.049</td>
<td>Furosemide → Albuterol</td>
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<tr>
<td>132</td>
<td>Moderate</td>
<td>0.351</td>
<td>0.023</td>
<td>Albuterol → Prednisone</td>
</tr>
</tbody>
</table>

Table 4. Verified DDI patterns mined by VMSP
Diabetes Home

Friends, Family, and Diabetes

YOUR SUPPORT CAN MAKE A REAL DIFFERENCE
Natural Experiments for Translation in Diabetes (NEXT-D) Study

Overall Objectives
To rigorously evaluate health policies and interventions coming from health care systems, businesses, communities, and health care legislation that may reduce diabetes risk, its complications, and health inequalities across broad segments of the U.S. population.

- Harvard Pilgrim
- UCLA
- Northwestern (with GPC CDRN)
CDC Monitors Data on Diabetes with Westat’s Expertise

2015-01-19
How is the nation doing in monitoring and managing diabetes? Westat will help answer that question for the Centers for Disease Control and Prevention (CDC) by assembling data to make state- and local-level population estimates of prevalence, risk factors, and complications over a 3-year period.

We will assemble, combine, and validate existing survey, administrative, and clinical data sources to produce data sets and models that take into account the complexity of combining data from disparate sources. We will be using data from 10 jurisdictions as well as national data sources.

The resulting databases, methods, and estimates will serve as a prototype for a sustainable system to monitor the outcomes of chronic disease prevention activities in all states. CDC and other stakeholders will be able to maintain and update the models as part of an enhanced approach to state and local chronic disease monitoring.

The selected jurisdictions include 9 states (Alabama, California, Florida, Louisiana, Maine, Massachusetts, Minnesota, North Dakota, and Utah) and 1 city (New York). These jurisdictions were chosen to represent varying levels of size, geography, data richness, and diabetes prevalence.