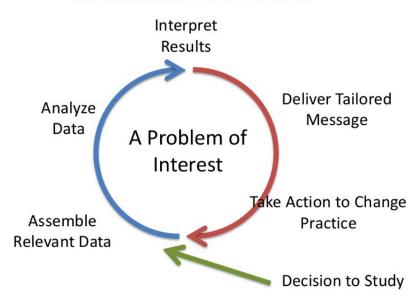
Better Evidence. Better Decisions. Better Health: e-Clinical Quality Measures

May 2016

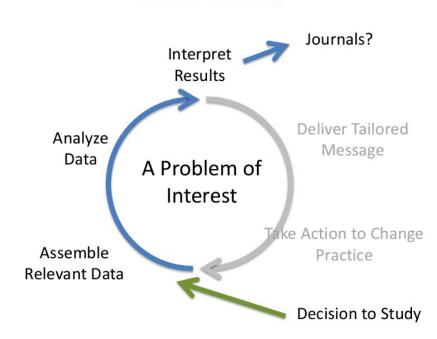


Learning Health System According to Chuck Friedman

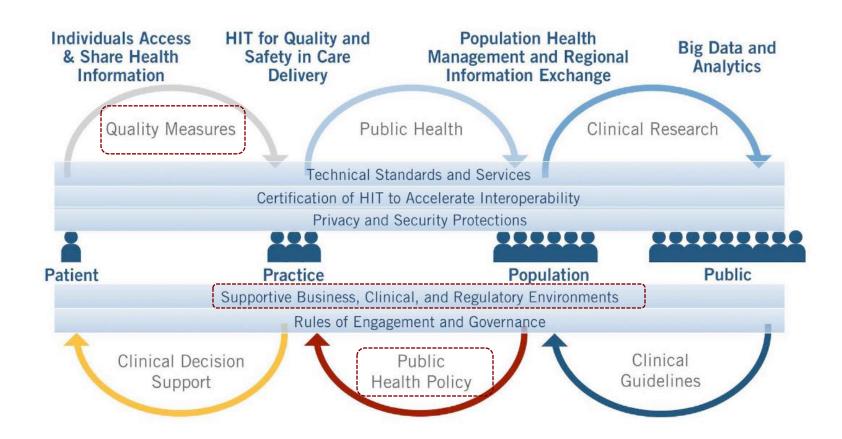
The LHS is Bigger than BD2K: It Must Do This



Not This



Learning Health System According to ONC



A Study Of The Impact Of Meaningful Use Clinical Quality Measures

Floyd Eisenberg, MD, MPH FACP (iParsimony LLC)
Caterina Lasome, PhD, MBA, RN, CPHIMS, LTC(Ret), USA (iON Informatics)
Aneel Advani, MD, MPH (everis USA)
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Patricia A. Craig, MS MIS (The Joint Commission)
Sharon Sprenger, RHIA, CPHQ, MPA (The Joint Commission)

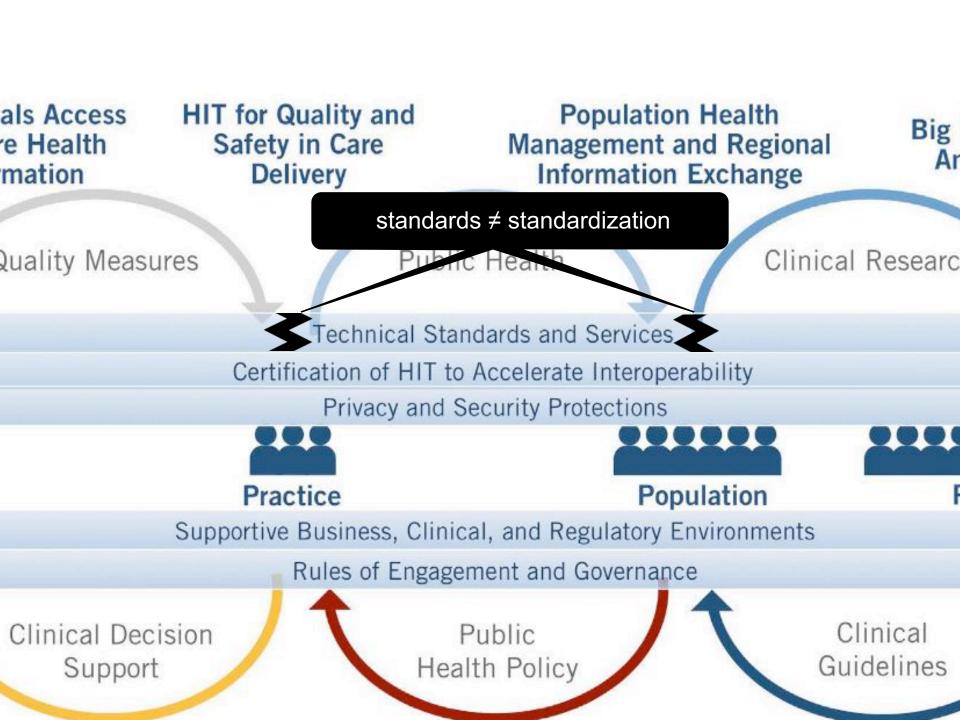
Technology Challenges

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

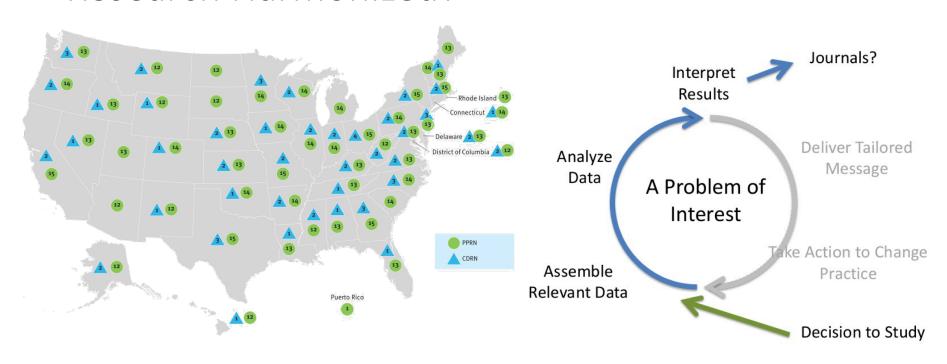
- Hospitals experienced significant difficulty implementing eCQM tools in their EHRs.
- The EHR could not draw relevant data from other systems

Clinical Challenges

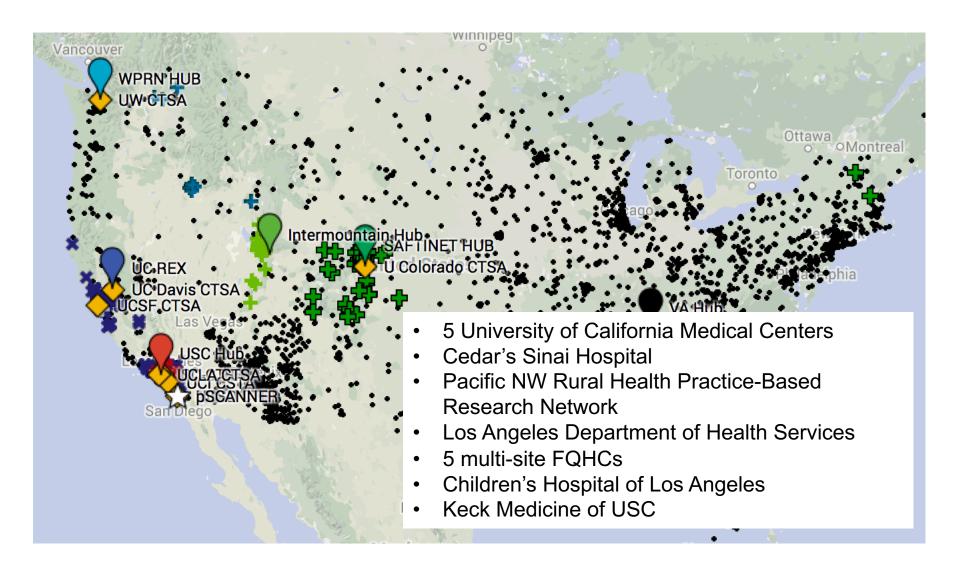
- eCQM reporting tools were poorly aligned with clinical workflow, necessitating the redesign of the patient care systems or the re-tooling of the reporting tools.
- Validation efforts were extensive, but not successful.
- Clinical staff did not trust the data.
- Rigid regulatory requirements caused 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.



Where are standards for HIT and Clinical Research Harmonized?



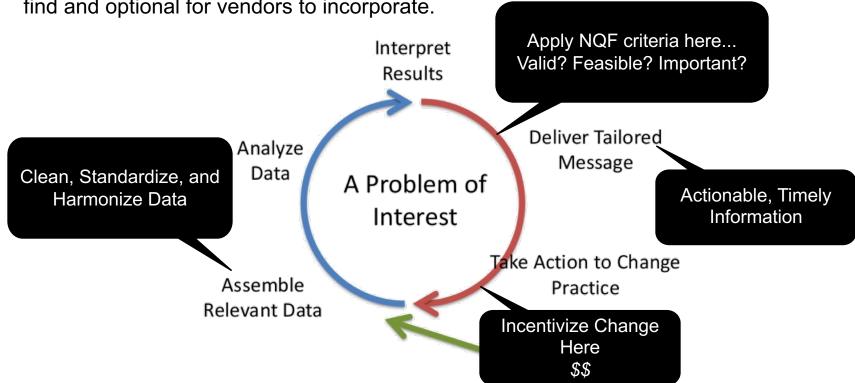
pSCANNER Network Connecting 21M patients' EHR Data



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.
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Reverse Engineering Measures of Clinical Care Quality: Sequential Pattern Mining

Hsuan Chiu^{1(⊠)} and Daniella Meeker²

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Table 4. Verified DDI patterns mined by VMSP

	PtnN	DDI	Coef	adjP	Drug sequence
Support	48	Moderate	0.353	0.001	Furosemide → Albuterol
	84	Moderate	0.450	0.000	salmeterol fluticasone
	132	Moderate	0.343	0.049	Azithromycin → Prednisone
	228	Severe	0.350	0.044	Acetaminophen → Warfarin
	348	Moderate	0.408	0.041	Lisinopril → Furosemide
MFS	120	Severe	0.349	0.001	Acetaminophen → Warfarin
	132	Severe	0.324	0.018	Furosemide → Warfarin
	288	Moderate	0.384	0.040	Albuterol → Prednisone
	300	Severe	0.384	0.045	Azithromycin → Levofloxacir
	312	Moderate	0.520	0.000	salmeterol fluticasone
	336	Moderate	0.396	0.047	Lisinopril → Furosemide
Maximized coverage	60	Moderate	0.216	0.039	salmeterol fluticasone
	72	Moderate	0.303	0.008	Lisinopril → Furosemide
	96	Moderate	0.228	0.049	Furosemide → Albuterol
	132	Moderate	0.351	0.023	Albuterol → Prednisone

http://uscdemo1.meliorix.com:5601/app/kibana#/dashboard/HQMF-Dashboard



CDC A-Z INDEX Y

Diabetes Home



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.