How to Plan and Perform Artificial Intelligence and Health Information Technologies Evaluation

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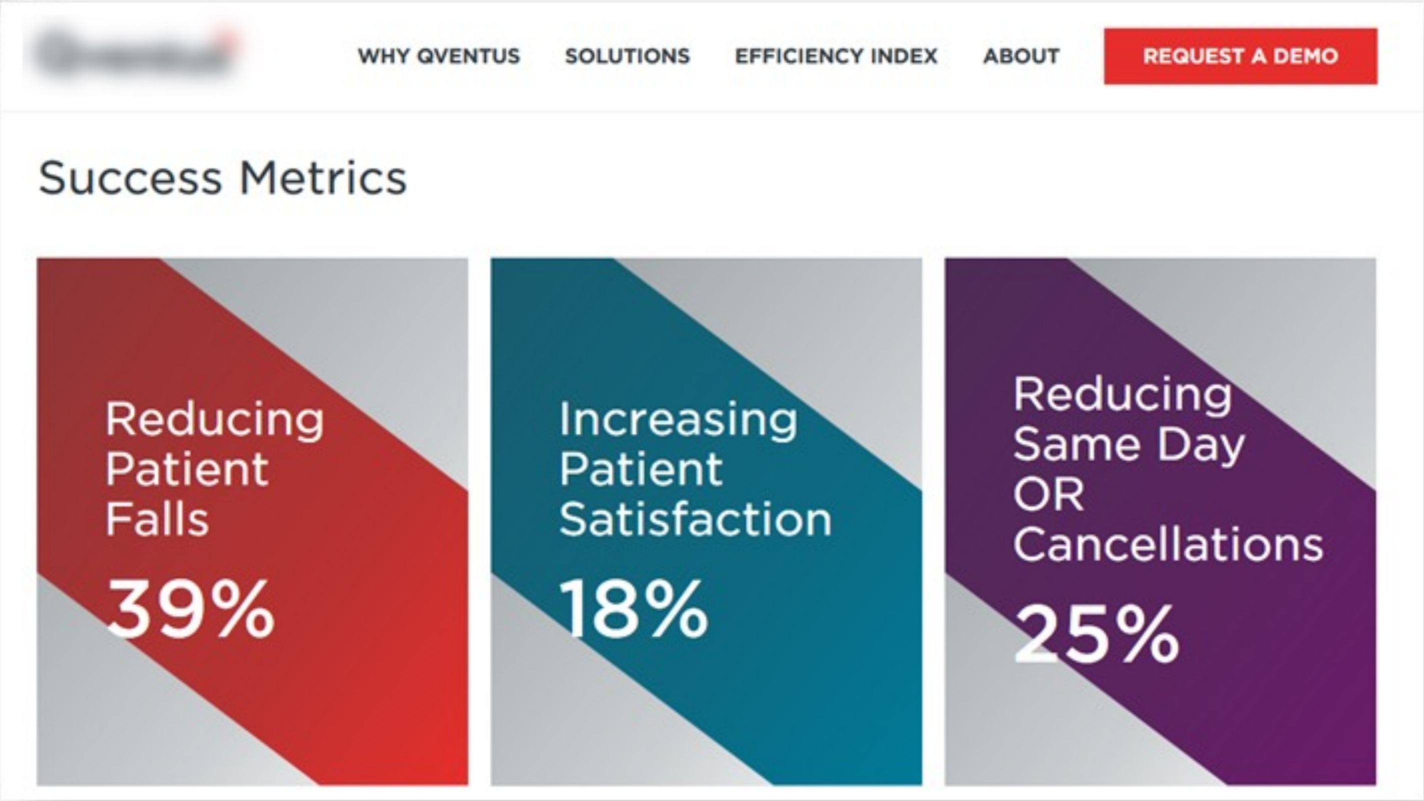
Objectives

1. Identify the value of technology evaluation;
2. Summarize basic terminologies, concepts and limitations in health information technology evaluation;
3. Recognize the methods and approaches in health information technology evaluation;

Why we evaluate Health Information Technologies?



1. **What is the setting?**
2. **What is the sample size?**
3. **What is the comparison group?**
4. **How biases controlled?**
5. **How statistical analysis was done?**

Clever marketing?

Reported effect

Publication bias

Funding bias

Measurement bias

Observer bias

Recall bias

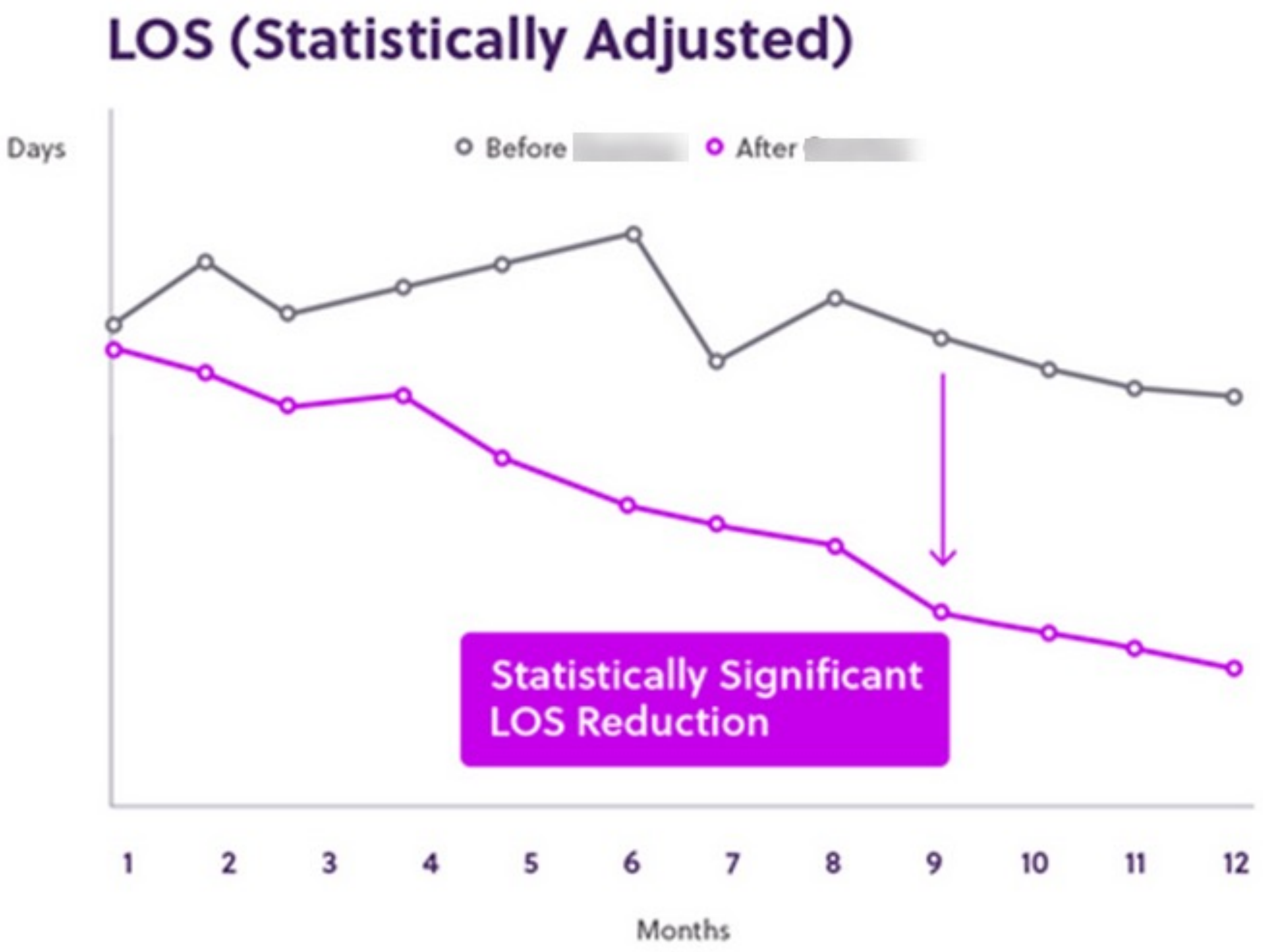
Selection bias

Confounding

Random error

Real causal effect

Photoshop tweaked…



Costs and Benefits of Health Information Technology

Evidence Reports/Technology Assessments, No. 132

Center Directors: Paul Shekelle, MD, PhD and Sally C Morton, PhD. Emmett B Keeler, PhD, Mathematician.

Rockville (MD): Agency for Healthcare Research and Quality (US); 2006 Apr.
Report No.: 06-E006

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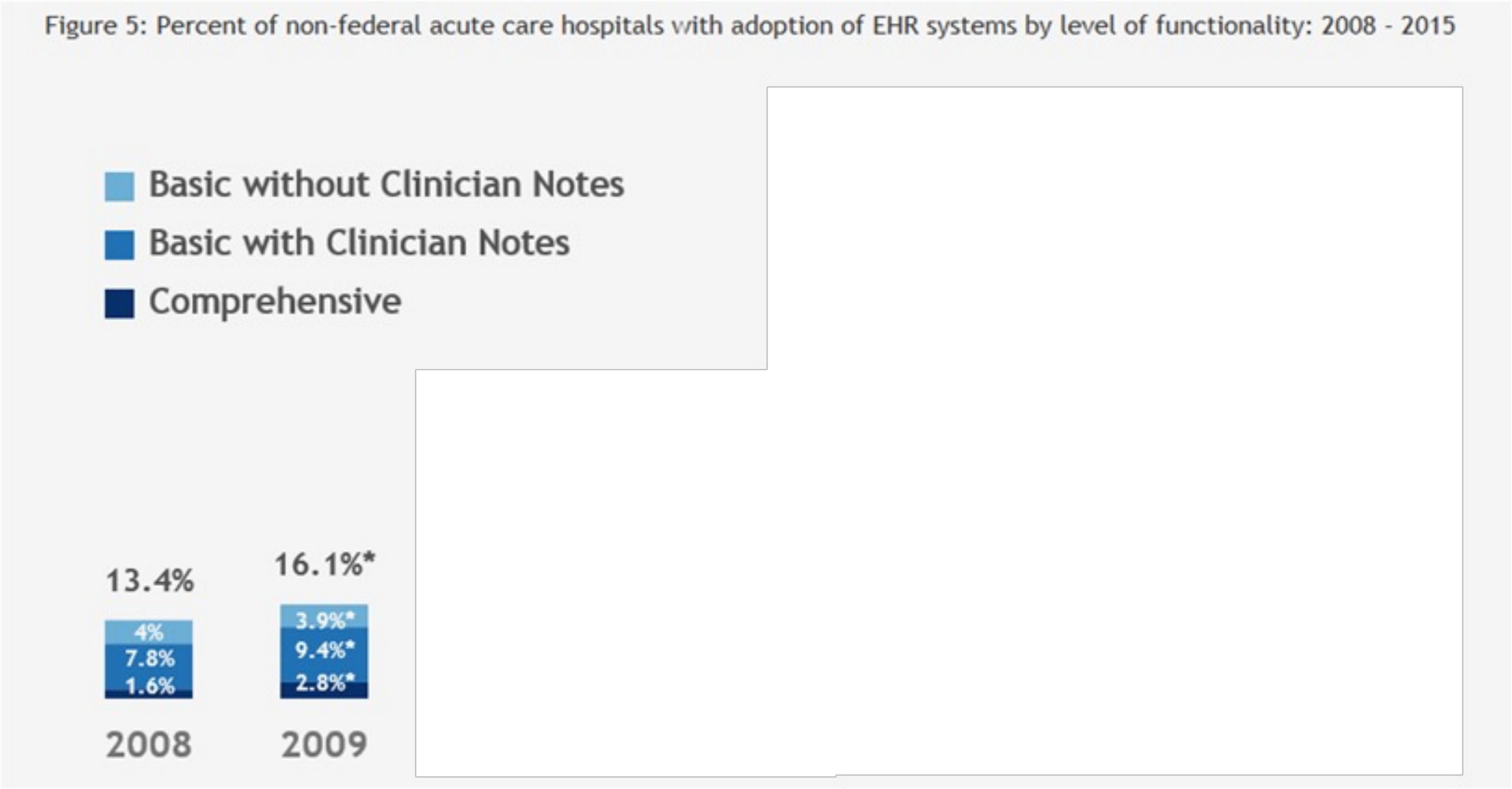
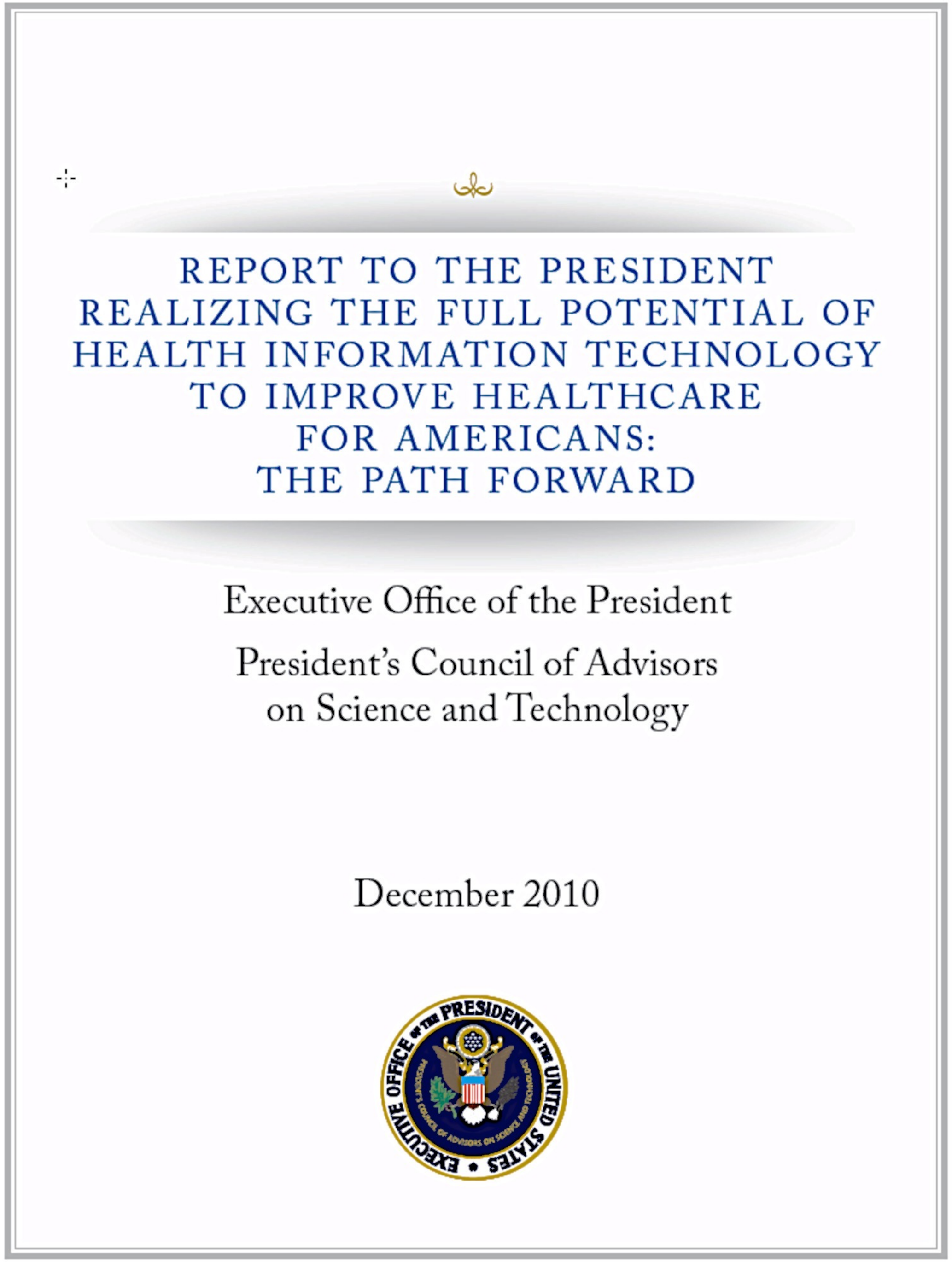
- Despite the heterogeneity in the analytic methods used, all cost-benefit analyses predicted substantial savings from EHR implementation: The quantifiable benefits are projected to outweigh the investment costs.
- **However, the predicted time needed to break even varied from three to as many as 13 years.**

EMR adoption statistics



- A **2009** survey of American Hospital Association (AHA) members found just **1.5%** of hospitals had a **comprehensive EHR** system.

Henry, J., Pylypchuck, Y., Searcy Y. & Patel V. (May 2016). Adoption of Electronic Health Record Systems among U.S. Non-Federal Acute Care Hospitals: 2008-2015. ONC Data Brief, no.35. Office of the National Coordinator for Health Information Technology: Washington DC. http://dashboard.healthit.gov/evaluations/data-briefs/non-federal-acute-care-hospital-ehr-adoption-2008-2015.php#citation



REPORT TO THE PRESIDENT
REALIZING THE FULL POTENTIAL OF
HEALTH INFORMATION TECHNOLOGY
TO IMPROVE HEALTHCARE
FOR AMERICANS:
THE PATH FORWARD

Executive Office of the President

President's Council of Advisors
on Science and Technology

December 2010

To **accelerate widespread adoption and use of EHRs**, the Health Information Technology for Economic and Clinical Health (HITECH) Act (2009), established.

Blumenthal D. Stimulating the adoption of health information technology. N Engl J Med. 2009 Apr 9;360(15):1477-9. PMID: 19321856.

2011

By Melinda Beeuwkes Buntin, Matthew F. Burke, Michael C. Hoaglin, and David Blumenthal

DOI: 10.1377/hlthaff.2011.0178
HEALTH AFFAIRS 30,
NO. 3 (2011): 464–471

The Benefits Of Health Information Technology: A Review Of The Recent Literature Shows Predominantly Positive Results

Melinda Beeuwkes Buntin (Melinda.buntin@hhs.gov) is director of the Office of Economic Analysis, Evaluation, and Modeling, Office of the National Coordinator for Health Information Technology (ONC), Department of Health and Human Services, in Washington, D.C.

Matthew F. Burke is a policy analyst at the ONC.

Michael C. Hoaglin is a former policy analyst at the ONC.

David Blumenthal is the national coordinator for health information technology.

ABSTRACT **An unprecedented federal effort is under way to boost the adoption of electronic health records and spur innovation in health care delivery. We reviewed the recent literature on health information technology to determine its effect on outcomes, including quality, efficiency, and provider satisfaction. We found that 92 percent of the recent articles on health information technology reached conclusions that were positive overall. We also found that the benefits of the technology are beginning to emerge in smaller practices and organizations, as well as in large organizations that were early adopters. However, dissatisfaction with electronic health records among some providers remains a problem and a barrier to achieving the potential of health information technology. These realities highlight the need for studies that document the challenging aspects of implementing health information technology more specifically and how these challenges might be addressed.**

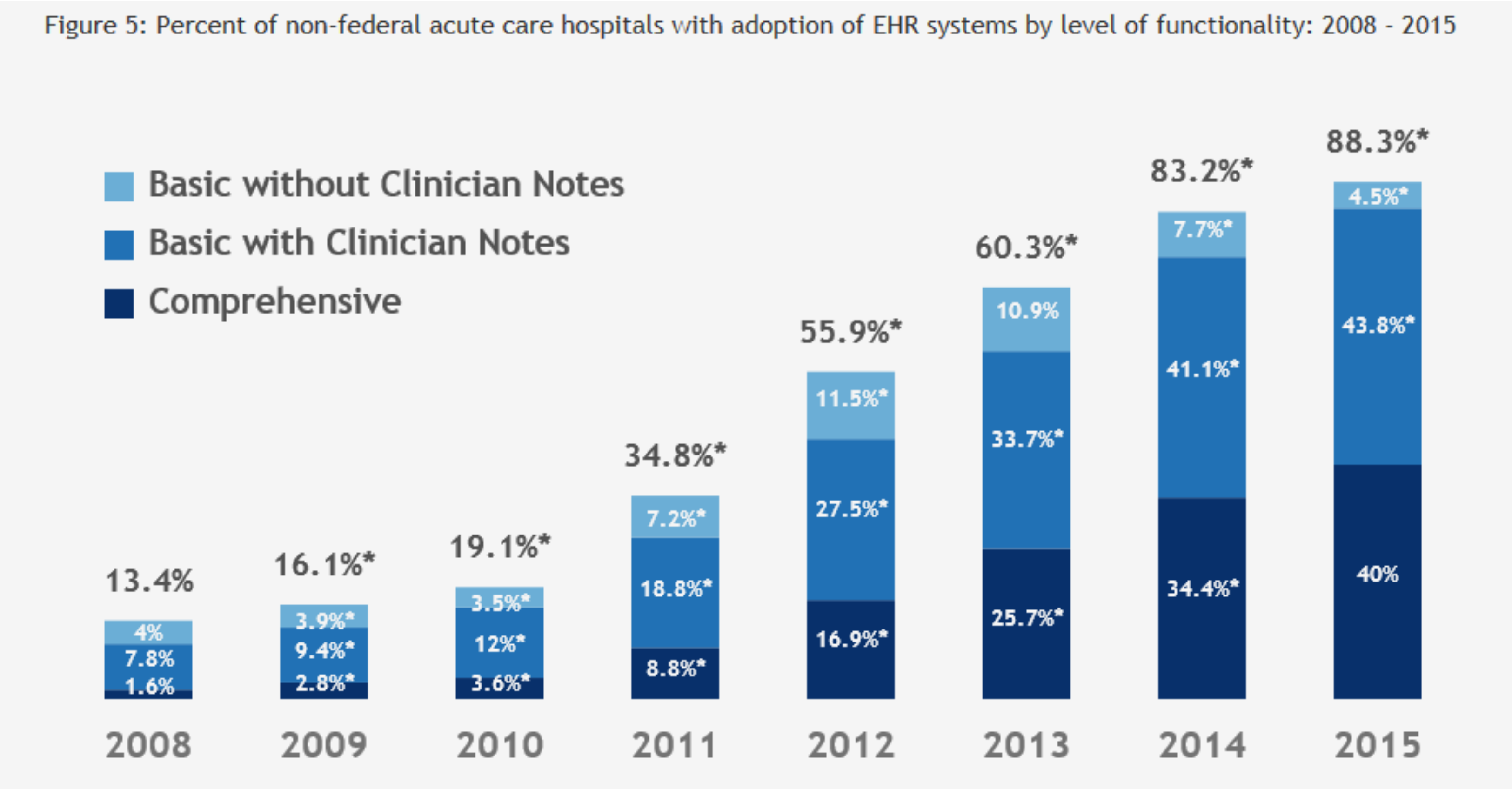
Health information technology (IT) has the potential to improve the health of individuals and the performance of providers, yielding improved quality, cost savings, and greater engagement by patients in their own health care.[1] Despite evidence of these benefits,[2] physicians' and hospitals' use of health IT and electronic health records is still low.[3,4]

To accelerate the use of health IT, in 2009 Congress passed and President Barack Obama signed into law the Health Information Technology for Economic and Clinical Health (HITECH) Act, as part of the American Recovery and Reinvestment Act. HITECH makes an estimated $14–27 billion in incentive payments available to hospitals and health professionals to adopt certified electronic health records and use them effectively in the course of care.[1] The legislation also established programs within the Office of the National Coordinator for Health Information Technology to guide physicians, hospitals, and other key entities as they adopt electronic health records and achieve so-called meaningful use, as spelled out in federal regulations.[5]

The legislation and subsequent regulations were designed to spur adoption and yield benefits from health information technology on a much broader scale than has been achieved to date. Building on that effort, the Affordable Care Act of 2010 underscored the importance of health IT in achieving goals related to health care quality and efficiency.

Specifically, establishing the Center for Medicare and Medicaid Innovation emphasized the importance of identifying and testing innovative payment and care delivery models. Many of the payment and care delivery model opportunities in the legislation, and in the initial projects specified by the Innovation Center, require an information technology infrastructure to coordinate care. For example, the medical home demonstrations project in federally qualified health centers that is an initial focus of the Innovation

EMR adoption statistics



- A **2009** survey of American Hospital Association (AHA) members found just **1.5%** of hospitals had a **comprehensive EHR** system… increased to **40%** in **2015**

Henry, J., Pylypchuck, Y., Searcy Y. & Patel V. (May 2016). Adoption of Electronic Health Record Systems among U.S. Non-Federal Acute Care Hospitals: 2008-2015. ONC Data Brief, no.35. Office of the National Coordinator for Health Information Technology: Washington DC. http://dashboard.healthit.gov/evaluations/data-briefs/non-federal-acute-care-hospital-ehr-adoption-2008-2015.php#citation

Key Findings

HIT's disappointing performance to date can be largely attributed to three factors:

1. Sluggish adoption of health IT systems
2. **Systems that are neither interoperable nor easy to use**
3. Failure of health care providers and institutions to reengineer care processes to reap the full benefits of health IT.

2015

Impact of the Electronic Medical Record on Mortality, Length of Stay, and Cost in the Hospital and ICU: A Systematic Review and Metaanalysis

Gwen Thompson, MD, MPH[1]; John C. O'Horo, MD, MPH[2]; Brian W. Pickering, MBBCh, MSc[3]; Vitaly Herasevich, MD, PhD, MSc[3]

Objective: To evaluate effects of health information technology in the inpatient and ICU on mortality, length of stay, and cost. Methodical evaluation of the impact of health information technology on outcomes is essential for institutions to make informed decisions regarding implementation.

Data Sources: EMBASE, Scopus, Medline, the Cochrane Review database, and Web of Science were searched from database inception through July 2013. Manual review of references of identified articles was also completed.

Study Selection: Selection criteria included a health information technology intervention such as computerized physician order entry, clinical decision support systems, and surveillance systems, an inpatient setting, and endpoints of mortality, length of stay, or cost. Studies were screened by three reviewers. Of the 2,803 studies screened, 45 met selection criteria (1.6%).

Data Extraction: Data were abstracted on the year, design, intervention type, system used, comparator, sample sizes, and effect on outcomes. Studies were abstracted independently by three reviewers.

Data Synthesis: There was a significant effect of surveillance systems on in-hospital mortality (odds ratio, 0.85; 95% CI, 0.76–0.94; I^2 = 59%). All other quantitative analyses of health information technology interventions effect on mortality and length of stay were not statistically significant. Cost was unable to be quantitatively evaluated. Qualitative synthesis of studies of each outcome demonstrated significant study heterogeneity and small clinical effects.

Conclusions: Electronic interventions were not shown to have a substantial effect on mortality, length of stay, or cost. This may be due to the small number of studies that were able to be aggregately analyzed due to the heterogeneity of study populations, interventions, and endpoints. Better evidence is needed to identify the most meaningful ways to implement and use health information technology and before a statement of the effect of these systems on patient outcomes can be made. (*Crit Care Med* 2015; XX:00–00)

Key Words: costs and cost analysis; electronic health records; length of stay; medical informatics; mortality

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Supplemental digital content is available for this article. Direct URL citations appear in the printed text and are provided in the HTML and PDF versions of this article on the journal's website (http://journals.lww.com/ccmjournal).

Drs. Pickering and Herasevich and their institutions licensed technology. Drs. Pickering and Herasevich receive royalties and have stock with Ambient Clinical Analytics Inc. Dr Pickering additionally is member on the Board of Directors of Ambient Clinical Analytics Inc.

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In recent years, the U.S. government has invested billions of dollars on the advancing of health information technology (HIT) through the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 (1, 2). This has been done with the hope that HIT will improve the health of Americans by providing better care while simultaneously lowering costs. Proponents of the electronic medical record (EMR) such as politicians, journalists, and the EMR industry claim that EMRs are able to fulfill this expectation. Statements by these groups are often made that EMRs "save lives" (3). However, there has never been a systematic review in inpatient settings supporting this claim.

Other systematic reviews of HIT have been conducted. However, they have focused on a particular intervention such as computerized physician order entry (CPOE) (4, 5), different settings such as ambulatory care (6, 7), a particular population (7), different endpoints such as medication prescription errors, medication safety (4, 5), or efficiency (6). No review has been conducted that evaluates all HIT interventions across all inpatient settings. The effect of various HIT interventions such as CPOE, clinical decision support (CDS) systems, and surveillance systems or "sniffers" are heterogeneous, each affecting a

Electronic interventions were not shown to have a substantial effect on mortality, length of stay, or cost.

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journal homepage: www.elsevier.com/locate/ijmedinf

Impact of electronic medical records (EMRs) on hospital productivity in Japan

Kozo Kaneko[a], Daisuke Onozuka[a], Hidetoshi Shibuta[b], Akihito Hagihara[a,*]

[a] *Department of Health Services Management and Policy, Kyushu University Graduate School of Medicine, Higashi-ku, Fukuoka 812-8582, Japan*
[b] *Department of Life and Welfare Information, Kindai University Kyushu Junior College, Iizuka, Fukuoka 820-8513, Japan*

Methods: This retrospective study focused on **658 municipal hospitals**. The study period was from 2006 to 2015. We analyzed the **labor productivity** and **multi-factor productivity (MFP).** Results: We found that the implementation of an EMR system had a significantly negative impact on MFP growth for the 'late adopters' (OR 0.51; 95%CI 0.31–0.82; p = 0.006). **No significant association was found between EMR implementation and labor productivity growth**.

Conclusion: EMR implementation has an adverse effect on the productivity of municipal hospitals in Japan.

Benefits of EHR

Improved Health Care Quality and Convenience for Providers

- Quick access to patient records
- Enhanced decision support
- Legible, complete documentation
- Safer prescribing

Improved Health Care Quality and Convenience for Patients

- Reduced need to fill out the same forms
- E-prescriptions electronically sent to pharmacy
- Patient portals
- Electronic referrals

- "Clinicians are often **given** technologies that were **designed by manufacturers** with **limited** usability **testing by clinicians**.
These technologies often **do not support the goals clinicians** are trying to achieve, **often hurt** rather than help productivity, and have a **neutral or negative impact** on patient safety."
- "Engineers and physicians **use different language**, apply **different theories** and methods, and employ **different performance measures.**"

Stephanie L. Reel is CIO and vice-provost for information technology at [Johns Hopkins University](#) and vice-president for information services for [Johns Hopkins Medicine](#) of Baltimore, MD

Standards in medicine vs standards in industry

- **Industry (IT)** standards determine whether the equipment can be **manufactured to an agreed standard** and whether the equipment does what it says it does.

- **Clinical** standards determine whether what the **equipment does is important**.

Major problem with EMR

1. Database centered systems
2. Time spent on interaction with technology
3. Satisfaction with EMR

Current EMR's are incapable of identifying information which the physician considers useful for decision making

2013

MD Anderson Taps IBM Watson to Power "Moon Shots" Mission

MD Anderson News Release 10/18/13

The University of Texas MD Anderson Cancer Center and IBM today announced that MD Anderson is using the IBM Watson cognitive computing system for its mission to eradicate cancer. Following a year-long collaboration, IBM and

2022

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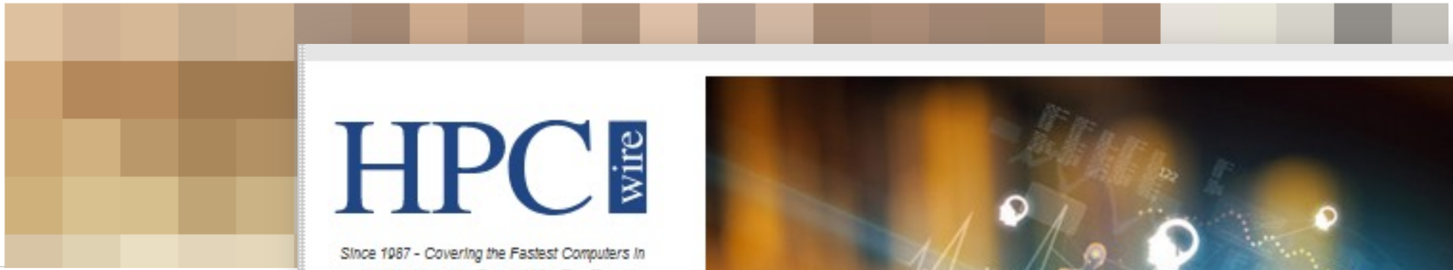
HARE

BUSINESS

IBM Sells Watson Health Assets to Investment Firm

The deal continues IBM's efforts to refocus core business around the cloud



HPCwire

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IBM Watson Health Finally Sold by IBM After 11 Months of Rumors

By Todd R. Weiss

January 21, 2022

IBM has sold its underachieving IBM Watson Health unit for an undisclosed price tag to a global investment firm after almost a year's worth of rumors that said IBM has been trying to exit this part of its business.

“Diagnosis is not the place to go. That’s something the experts do pretty well. It’s a hard task, and no matter how well you do it with AI, it’s not going to displace the expert practitioner.”

–AJAY ROYYURU, IBM’s vice president of health care and life sciences research

DATE		IBM PARTNER	PROJECT	CURRENT STATUS
2011	Feb.	Nuance Communications	Diagnostic tool and clinical-decision support tools	No tools in use
	Sept.	WellPoint (now Anthem)	Clinical-decision support tools	No tools in use
2012	March	Memorial Sloan Kettering Cancer Center	Clinical-decision support tool for cancer	Watson for Oncology
	Oct.	Cleveland Clinic	Training tool for medical students; clinical-decision support tool	No tools in use
2013	Oct.	MD Anderson Cancer Center	Clinical-decision support tool for cancer	No tool in use
2014	March	New York Genome Center	Genomic-analysis tool for brain cancer	No tool in use
	June	GenieMD	Consumer app for personalized medical advice	No app available
	Sept.	Mayo Clinic	Clinical-trial matching tool	Watson for Clinical Trial Matching
2015	April	Johnson & Johnson	Consumer app for pre- and postoperation coaching; consumer app for managing chronic conditions	No apps available
	April	Medtronic	Consumer app for personalized diabetes management	Sugar.IQ app
	May	Epic	Clinical-decision support tool	No tool in use
	May	University of North Carolina, others	Genomic-analysis tool for cancer	Watson for Genomics
	July	CVS Health	Care-management tool for chronic conditions	No tool in use
	Sept.	Teva Pharmaceuticals	Drug-development tool; consumer app for managing chronic conditions	No tool in use; no app available
	Sept.	Boston Children's Hospital	Clinical-decision support tool for rare pediatric diseases	No tool in use
	Dec.	Nutrina	Consumer app for personalized nutrition advice during pregnancy	No app available
	Dec.	Novo Nordisk	Consumer app for diabetes management	No app available
2016	Jan.	Under Armour	Consumer app for personalized athletic coaching	No app available
	Feb.	American Heart Association	Consumer app for workplace health	No app available
	April	American Cancer Society	Consumer app for personalized guidance during cancer treatment	No app available
	June	American Diabetes Association	Consumer app for personalized diabetes management	No app available
	Oct.	Quest Diagnostics	Genomic-analysis tool for cancer	Watson for Genomics from Quest Diagnostics
	Nov.	Celgene Corp.	Drug-safety analysis tool	No tool in use
2017	May	MAP Health Management	Relapse-prediction tool for substance abuse	No tool in use

E. Strickland, "IBM Watson, heal thyself: How IBM overpromised and underdelivered on AI health care," in IEEE Spectrum, vol. 56, no. 4, pp. 24-31, April 2019, doi: 10.1109/MSPEC.2019.8678513. https://ieeexplore.ieee.org/document/8678513

HEALTH TECH

Hospitals are using AI to predict the decline of Covid-19 patients — before knowing it works

By CASEY ROSS / APRIL 24, 2020

Formerly shuttered St. Vincent Medical Center in Los Angeles was reopened earlier this month to help treat patients during the Covid-19 pandemic.
DAMIAN DOVARGANES/AP

Dozens of hospitals across the country are using an artificial intelligence system created by Epic, the big electronic health record vendor, to predict which Covid-19 patients will become critically ill, even as many are struggling to validate the tool's effectiveness on those with the new disease.

The rapid uptake of Epic's deterioration index is a sign of the challenges imposed by the pandemic: Normally hospitals would take time to test the tool on hundreds of patients, refine the algorithm underlying it, and then adjust care practices to implement it in their clinics.

Google and Harvard release COVID-19 prediction models

Kyle Wiggers @Kyle_L_Wiggers August 3, 2020 9:40 AM AI

Google Cloud Next 2019 Image Credit: Khari Johnson / VentureBeat

In partnership with the Harvard Global Health Institute, Google today released the COVID-19 Public Forecasts, a set of models that provide projections of COVID-19 cases, deaths, ICU utilization, ventilator availability, and other metrics over the next 14 days for U.S. counties and states. The models are trained on public data such as those from Johns Hopkins University, Descartes Labs, and the United States Census Bureau, and Google says they'll continue to be updated with guidance from its collaborators at Harvard.

Artificial intelligence / Machine learning

Hundreds of AI tools have been built to catch covid. None of them helped.

Some have been used in hospitals, despite not being properly tested. But the pandemic could help make medical AI better.

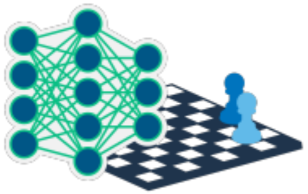
by **Will Douglas Heaven** July 30, 2021

When covid-19 struck Europe in March 2020, hospitals were plunged into a health crisis that was still badly understood. "Doctors really didn't have a clue how to manage these patients," says Laure Wynants, an epidemiologist at Maastricht University in the Netherlands, who studies predictive tools.

But there was data coming out of China, which had a four-month head start in the race to beat the pandemic. If machine-learning algorithms could be

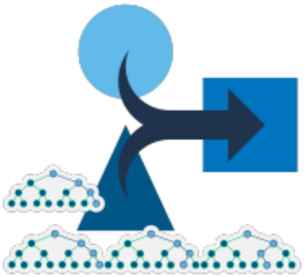
https://www.technologyreview.com/2021/07/30/1030329/machine-learning-ai-failed-covid-hospital-diagnosis-pandemic

Not a novel



1950s–1970s

Neural Networks



1980s–2010s

Machine Learning

Present Day

Deep Learning

- **1956** - The term **AI was coined** in.
- **1960**s - US DoD began training computers to **mimic basic human reasoning**.
- **1970**s - DARPA completed **street mapping** project.
- **2003** - DARPA produced **intelligent personal assistant** - long before Siri, Alexa.

1980

Chapter 2

Artificial Intelligence in Medicine (AIM)

The development of expert critiquing systems is part of a growing field involving numerous projects applying artificial intelligence in medicine. This work has been in progress for the past 15 years (Clancey and Shortliffe 1984; Kulikowski 1980; Shortliffe et al. 1979; Szolovits 1982). This chapter gives an overview of these projects. It then discusses the field of AI as a whole. Finally, the chapter discusses how critiquing itself can be performed at different levels of complexity. The critiquing research described in this book focusses on the more complex end of this spectrum.

The NEW ENGLAND JOURNAL of MEDICINE

SOUNDING BOARD ARCHIVE

Artificial Intelligence in Medicine

William B. Schwartz, M.D., Ramesh S. Patil, Ph.D., and Peter Szolovits, Ph.D.

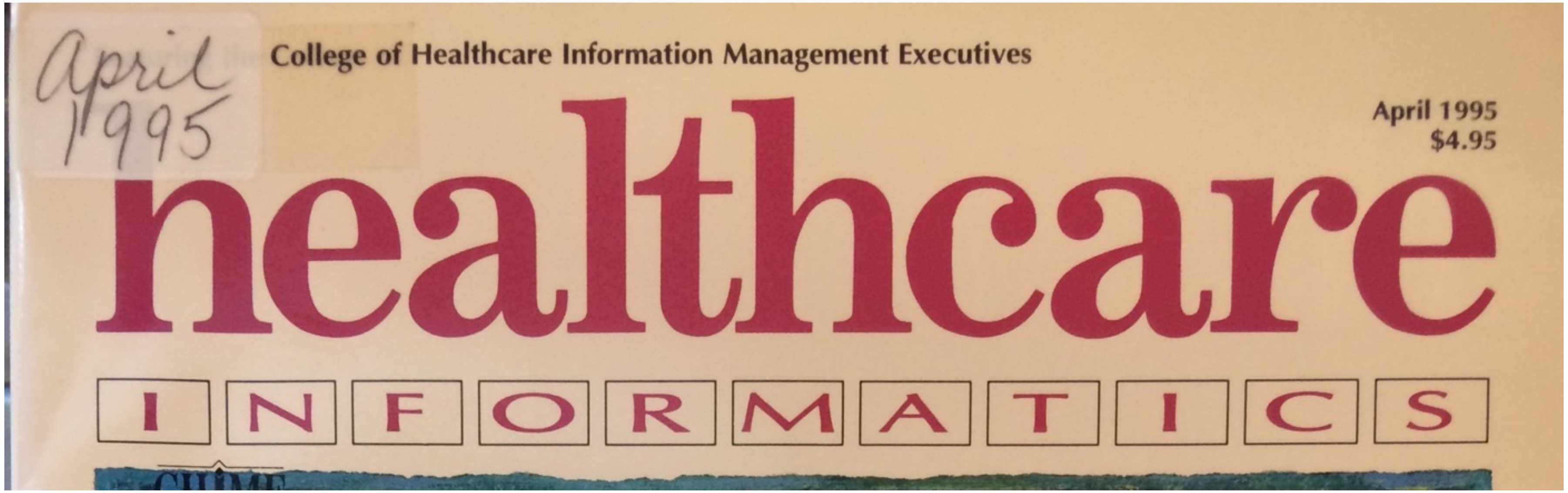
Article

33 References 83 Citing Articles

March 12, 1987
N Engl J Med 1987; 316:685-688
DOI: 10.1056/NEJM198703123161109

AFTER HEARING FOR SEVERAL DECADES THAT COMPUTERS WILL SOON BE ABLE TO assist with difficult diagnoses, the practicing physician may well wonder why the revolution has not occurred. Skepticism at this point is understandable. Few, if any, programs currently have active roles as consultants to physicians. The story behind these unfulfilled expectations is instructive and, we believe, offers hope for the future.

Research on computer-aided diagnosis began in the 1960s with high hopes that difficult clinical problems might yield to mathematical formalisms. Most work therefore centered on the application of flow charts, Boolean algebra, pattern matching, and decision analysis to the diagnostic process.[1] Except in extremely narrow clinical domains, each of these techniques proved to have little or no practical value. Most observers came to believe that for a program to have expert capability, it must in some fashion mimic the behavior of experts. Early work on computer-aided diagnosis was thus largely discarded, and in the early 1970s attention shifted to the study of the actual problem-solving behavior of experienced clinicians.[2 3 4 5] The resulting insights have subsequently been used to construct models of clinical problem solving that, in turn, have been converted into so-called artificial-intelligence programs or expert systems.[1, 6, 7]


april 1995
College of Healthcare Information Management Executives
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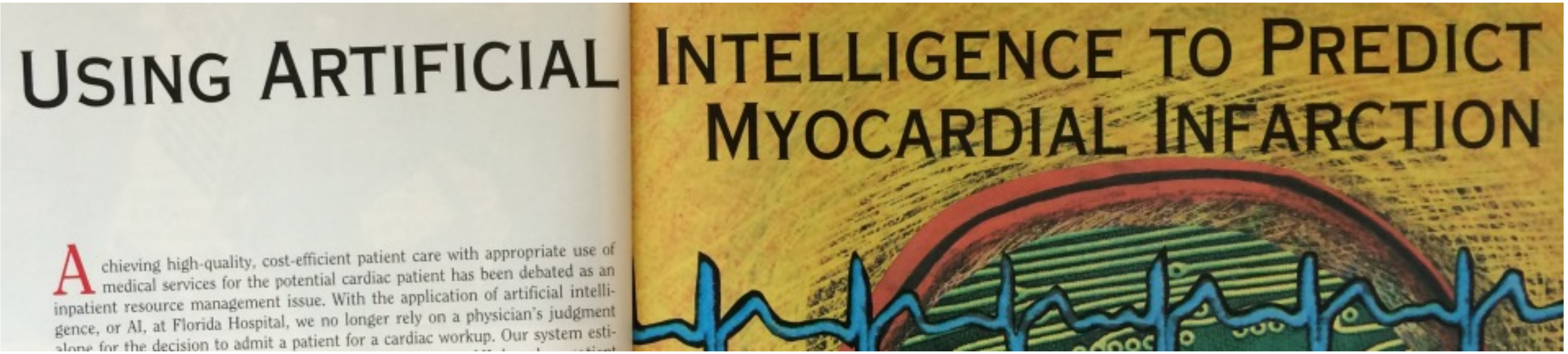
INFORMATICS


USING ARTIFICIAL INTELLIGENCE TO PREDICT MYOCARDIAL INFARCTION
Achieving high-quality, cost-efficient patient care with appropriate use of medical services for the potential cardiac patient has been debated as an inpatient resource management issue. With the application of artificial intelligence, or AI, at Florida Hospital, we no longer rely on a physician's judgment alone for the decision to admit a patient for a cardiac workup. Our system esti-

1995

Why AI has become more popular today?

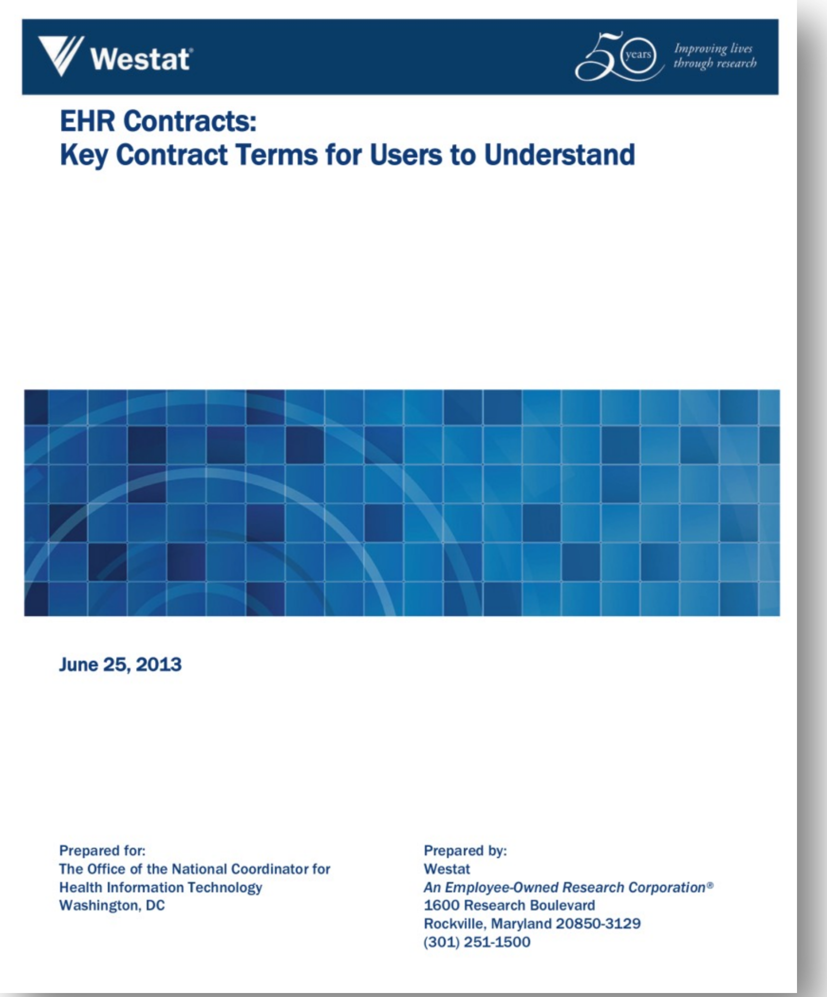
Increase data volumes and storage

Improvements in computing power

CDS (Artificial intelligence) agreement

- Customer agrees to defend, indemnify and hold harmless EHR technology developer and its employees, officers, directors, or contractors (collectively, "**EHR technology developer** Indemnitees") **from any claim** by or on behalf **of any patient** of Customer, which is **brought against any EHR technology developer** Indemnitee regardless of the cause if such claim arises **for any reason** whatsoever out of the operation of the **EHR Software licensed** to Customer under this Agreement.

This document explains a few key EHR contract terms and what you need to know about them.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50 years Improving lives through research

EHR Contracts:
Key Contract Terms for Users to Understand

June 25, 2013

Prepared for:
The Office of the National Coordinator for
Health Information Technology
Washington, DC

Prepared by:
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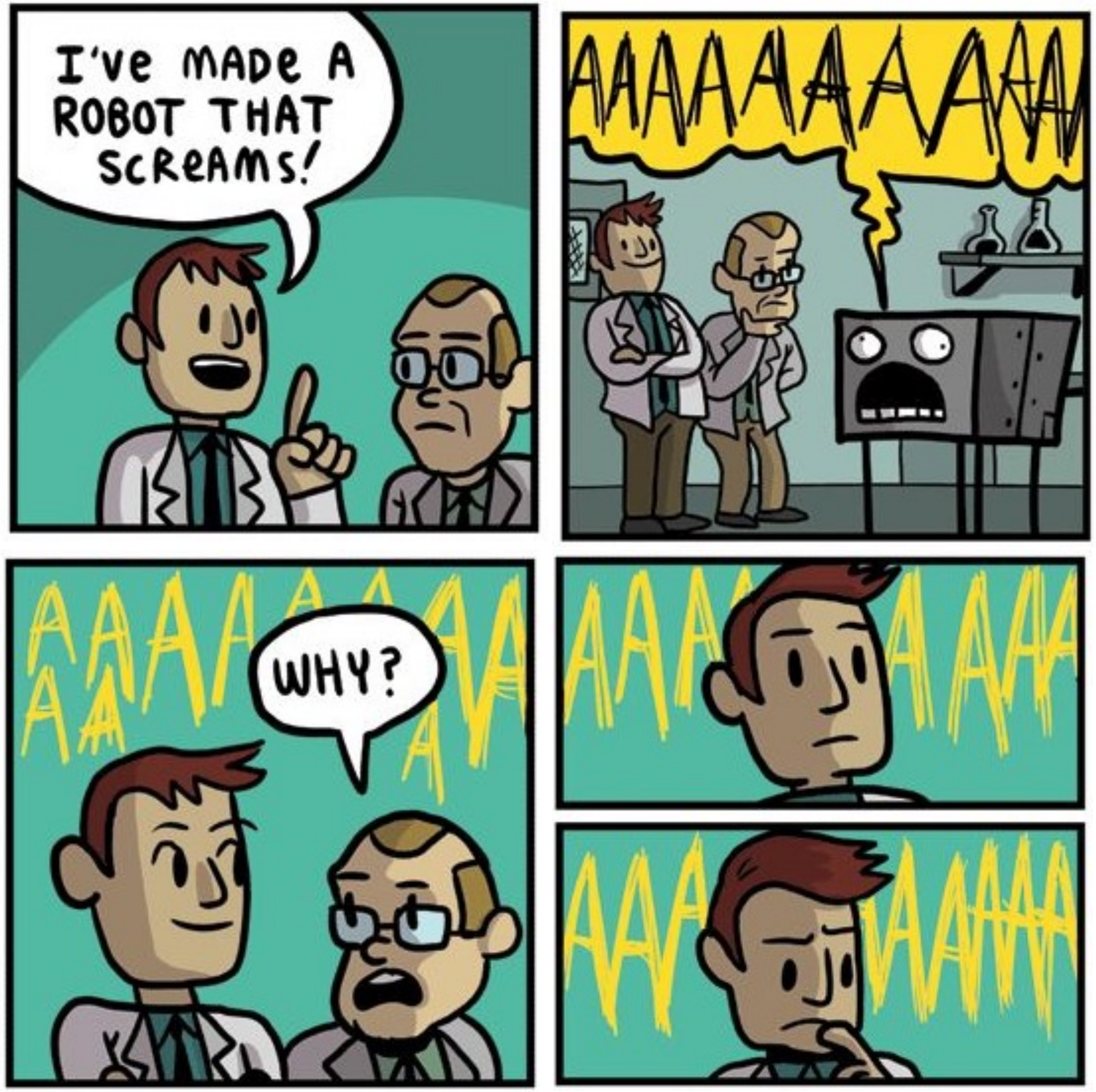
An Employee-Owned Research Corporation®
1600 Research Boulevard
Rockville, Maryland 20850-3129
(301) 251-1500

https://www.healthit.gov/sites/default/files/ehr_contracting_terms_final_508_compliant.pdf

What is evaluation?

Applied Clinical Informatics fundamentals



Evaluation, Assessment, Research

- **WHAT IS EVALUATION?**
  Evaluation is a system of measurement or set of criteria to see **if an existing technology is working** or **needs improvement**, according to **its purpose** and objectives.

- **WHAT IS ASSESSMENT?**
  Assessment is an process of measuring **existing** technology towards **claimed goals** and objectives.

- **WHAT IS RESEARCH?**
  Research is the **systematic process of developing new knowledge** used collecting and analyzing data about a particular subject.

Why must we evaluate medical technologies?

1. Is the technology safe?
2. Does the technology do what it supposed to do?
3. Is what it does useful?
4. Can it be usefully applied in my practice?

Guyatt GH et al. A framework for clinical evaluation of diagnostic technologies (1986) PMID: 3512062

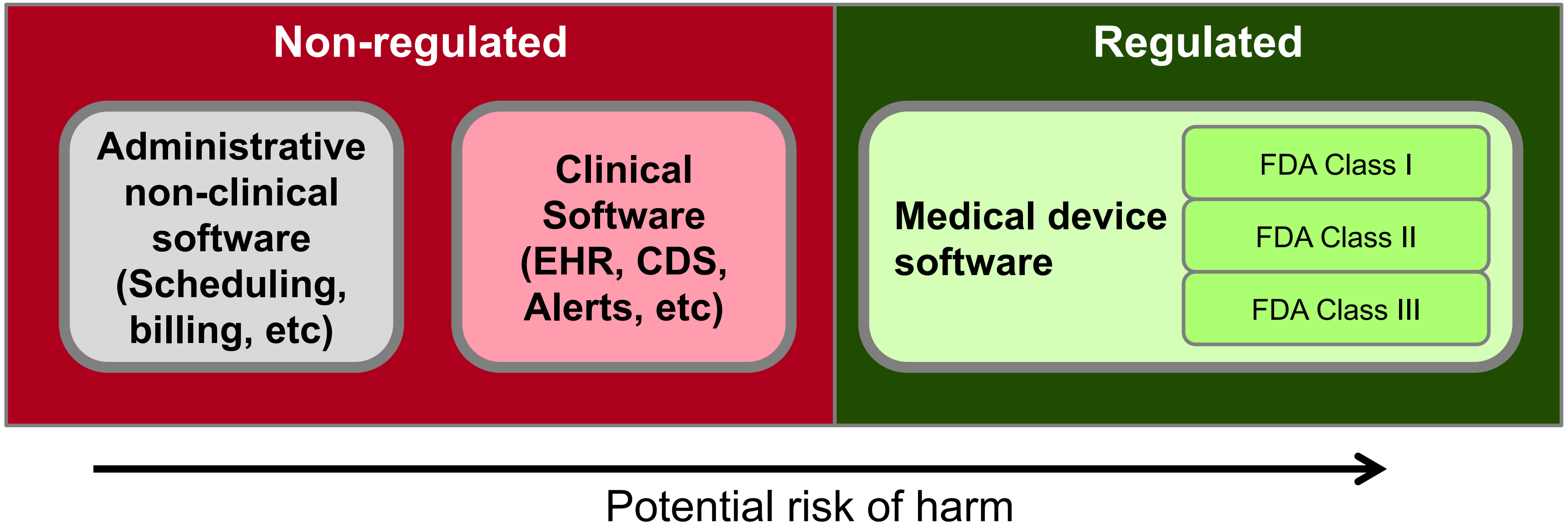
Why is not FDA ?

- The FDA is responsible for **protecting and promoting public health through the regulation and supervision** of food safety, tobacco products, dietary supplements, prescription and over-the-counter pharmaceutical drugs (medications), vaccines, biopharmaceuticals, blood transfusions, **medical devices**, electromagnetic radiation emitting devices (ERED), and veterinary products.

Simply required that the device:

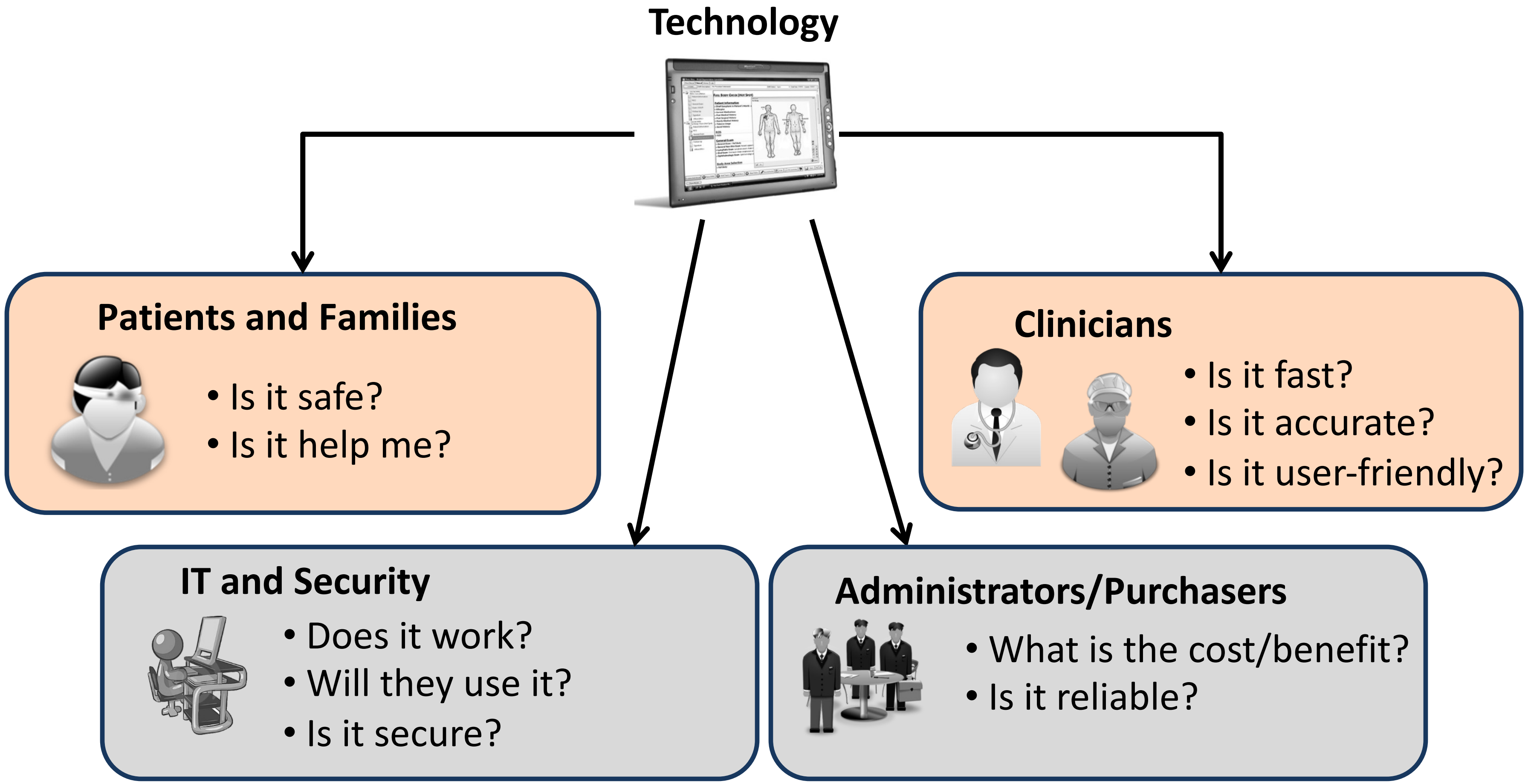
1. **Is safe**
2. **Performs the function claimed**

Current regulatory space for HIT



What is important to evaluate?

HIT Stakeholders



Herasevich V, Pickering BW Health Information Technology Evaluation Handbook: From Meaningful Use to Meaningful Outcome, 2017, 208 pages, CRC Press, ISBN 978-1498766470

Main criteria for rigorous evaluation

1. **Technologic capability:** The ability of the technology to perform to specifications in a laboratory setting has been demonstrated.
2. **Range of possible uses:** The technology promises to provide important information in a range of clinical situations.
3. **Diagnostic accuracy:** The technology provides information that allows healthcare workers to make a more accurate assessment regarding the presence and severity of disease.
4. **Impact on healthcare providers:** The technology allows healthcare workers to be more confident of their diagnoses, thereby decreasing their anxiety and increasing their comfort.
5. **Therapeutic impact:** The therapeutic decisions made by healthcare providers are altered as a result of the application of the technology.
6. **Patient outcome:** Application of the technology results in benefits to the patient.

Guyatt GH, et al. A framework for clinical evaluation of diagnostic technologies. CMAJ. 1986;134(6):587–594.

Define and prioritize study questions as clinical oriented outcomes of interest

- **Better health:** Rate of ICU acquired complications, discharge home, hospital mortality, ICU and hospital readmission

- **Better care:** Adherence to and appropriateness of processes of care, provider satisfaction

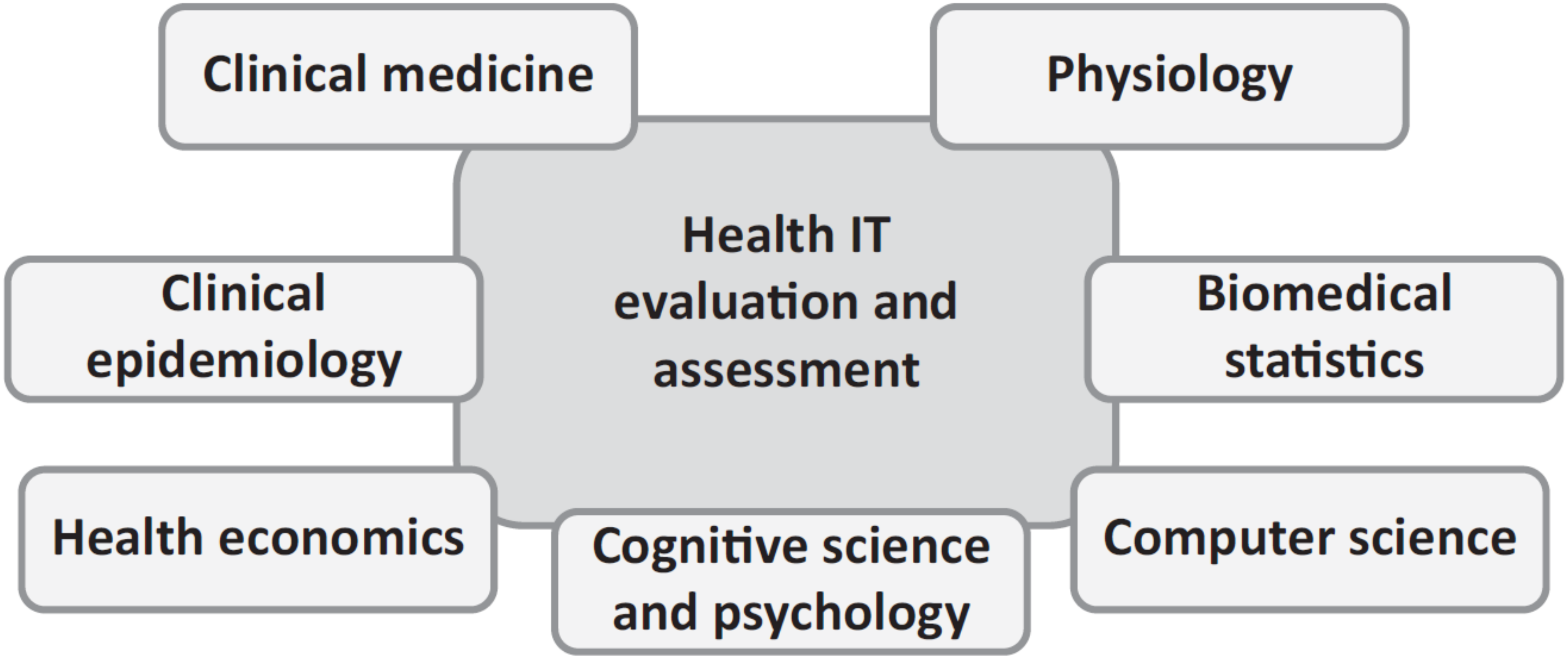
- **Lower cost:** resource utilization, severity adjusted length of ICU and hospital stay and cost

Methodology

Structure of Evaluation Studies

1. Define the health IT (**application**, system) to be studied.
2. Define the **stakeholders** whose questions should be addressed.
3. Define and prioritize **study questions**.
4. Choose the **appropriate methodology** to minimize bias and address generalizability.
5. Select reliable, valid **measurement methods**.
6. **Carry out** the study.
7. Prepare publication for **results dissemination** (report, press release, publication in scientific journal).

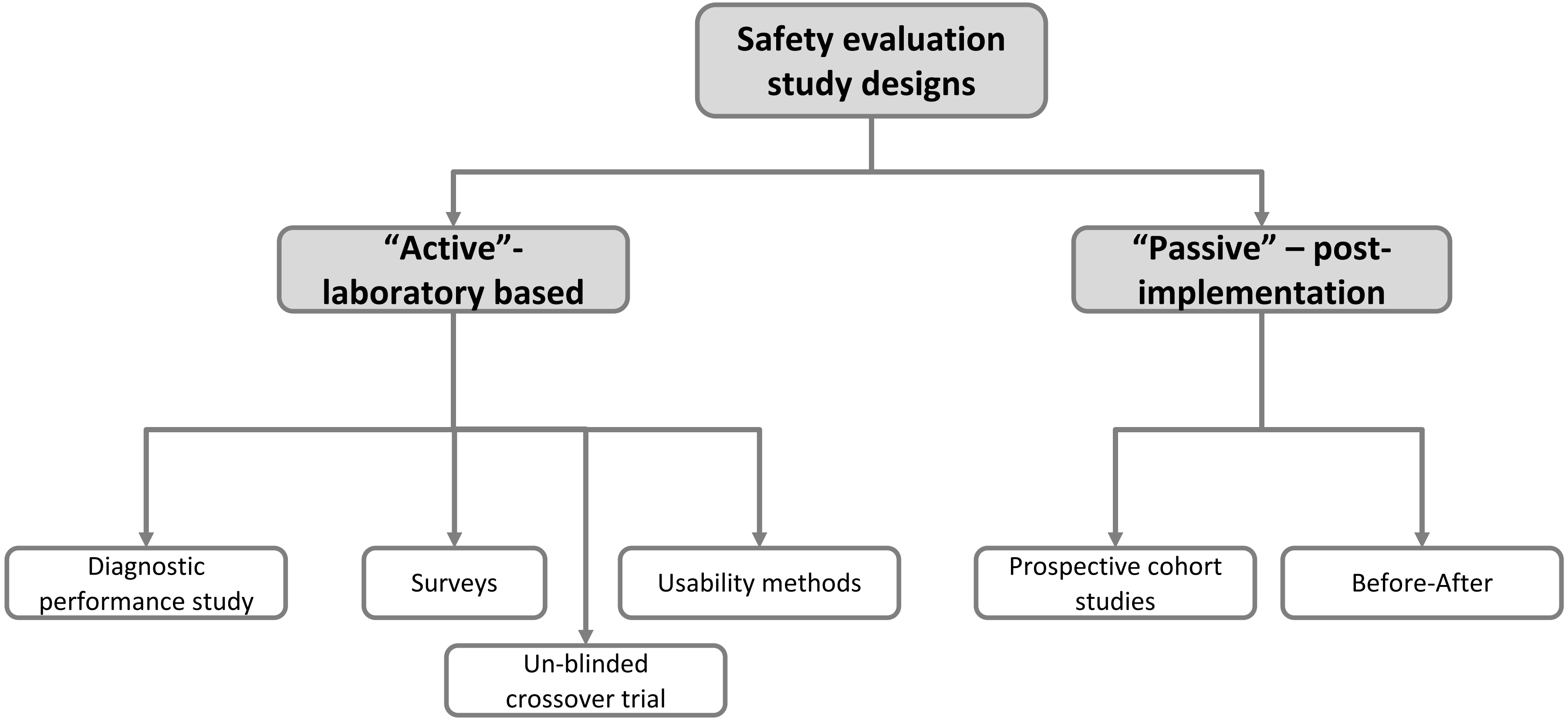
Expertise required for HIT evaluation



Framework for a clinically meaningful HIT evaluation.

1. **Safety**
   Evaluate the technology itself and any action that arises from its use
2. **Efficacy**
   Measure what the technology is supposed to do under ideal conditions
3. **Effectiveness**
   Measure what the technology is supposed to do under average conditions
4. **Efficiency (Cost)**
   Determine the resources needed to provide the technology and achieve a return on investment

Safety evaluation



Efficacy and Effectiveness Evaluation

- **Efficacy:** Measures what it is supposed to measure under an **ideal condition**. Efficacy is the measurement of the ability of the intervention to have effects without necessarily being relevant to patients. Such studies are performed in a highly controlled environment with highly compliant participants. In clinical research, such studies are **called explanatory trials** or **Phase I or II** of clinical trials. In HIT evaluation, we can call them **"lab studies".**

- **Effectiveness:** Measures what it is supposed to measure under an **average condition**. Effectiveness is the ability of an intervention to have **effects on patients** in normal clinical conditions. In clinical research, such studies are called **pragmatic trials** or **Phase III or IV of clinical trials**. In HIT evaluation, these studies include "**live**" implementation.

In fact, effectiveness is widely used in usability studies but with a meaning different from that used in the world of epidemiological research

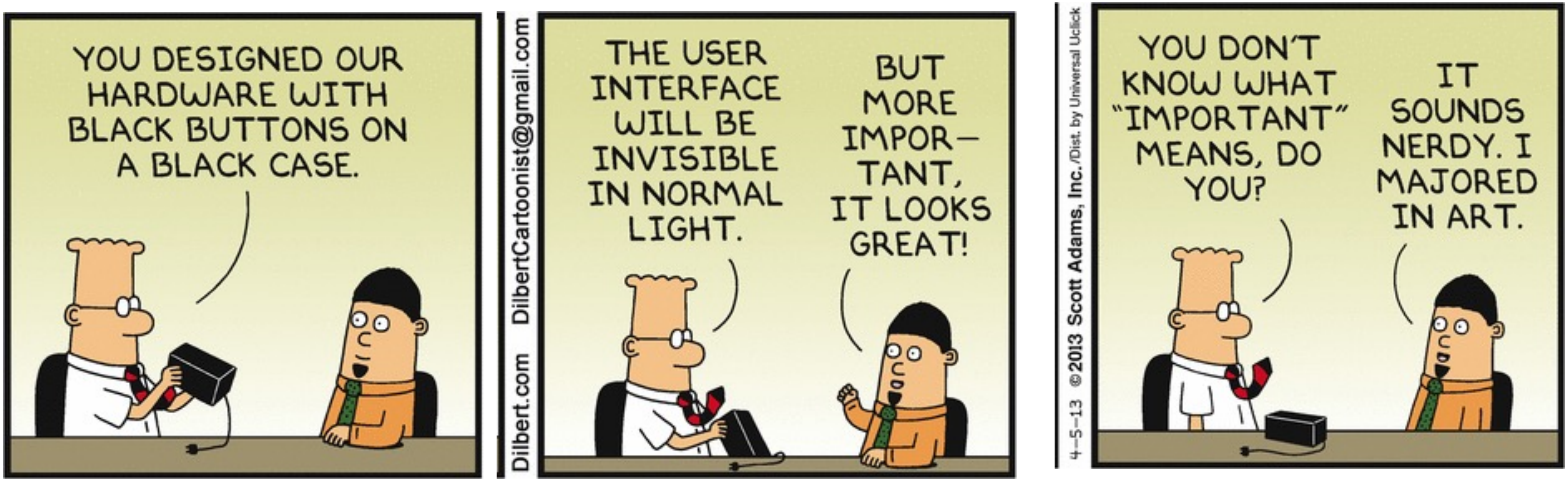
Efficacy and Effectiveness Evaluation

	Efficacy	Effectiveness
Setting	Ideal	Average
Clinical research equivalent	Phase I trial Phase II trial	Phase III trial Phase IV trial
	“Laboratory”	**“Live”**

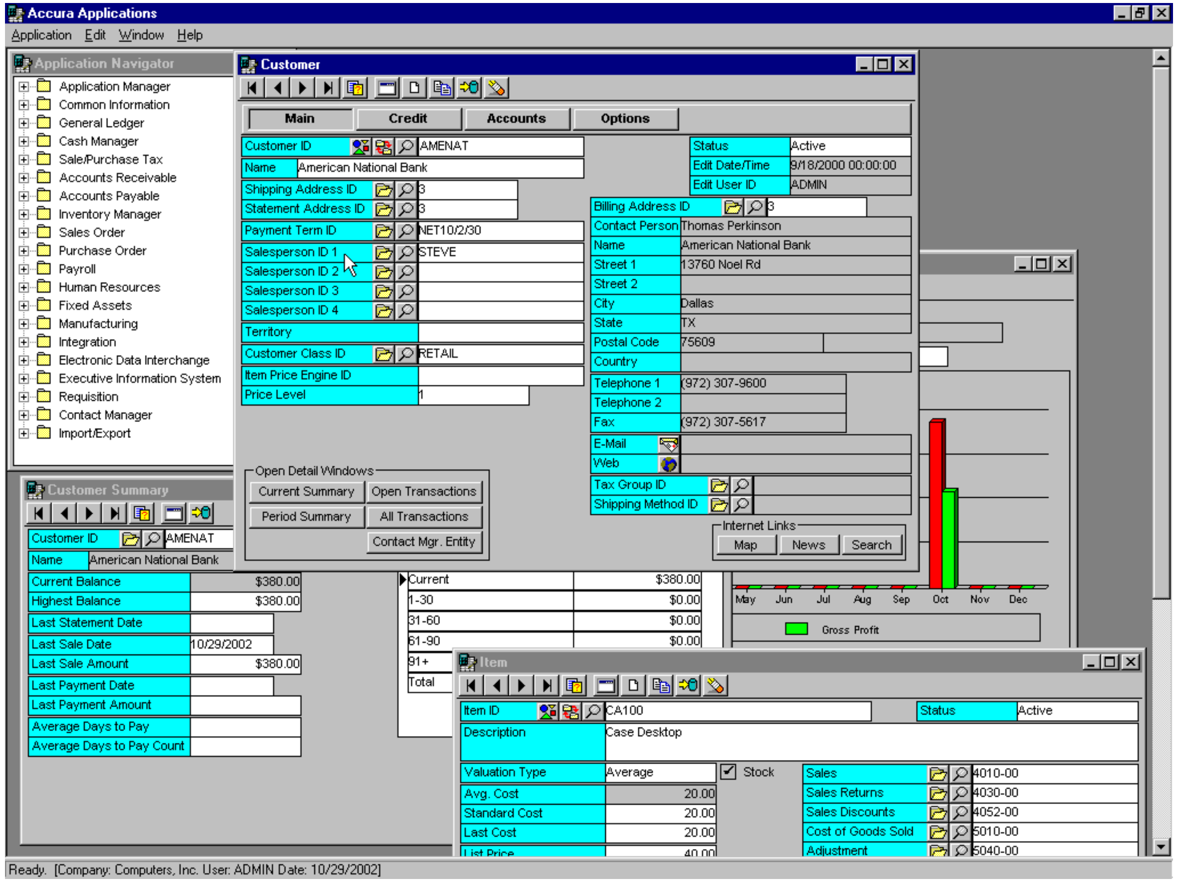
Ultimate Outcome Measures

1. Reduced mortality
2. Improved symptom control
3. Improved patient satisfaction

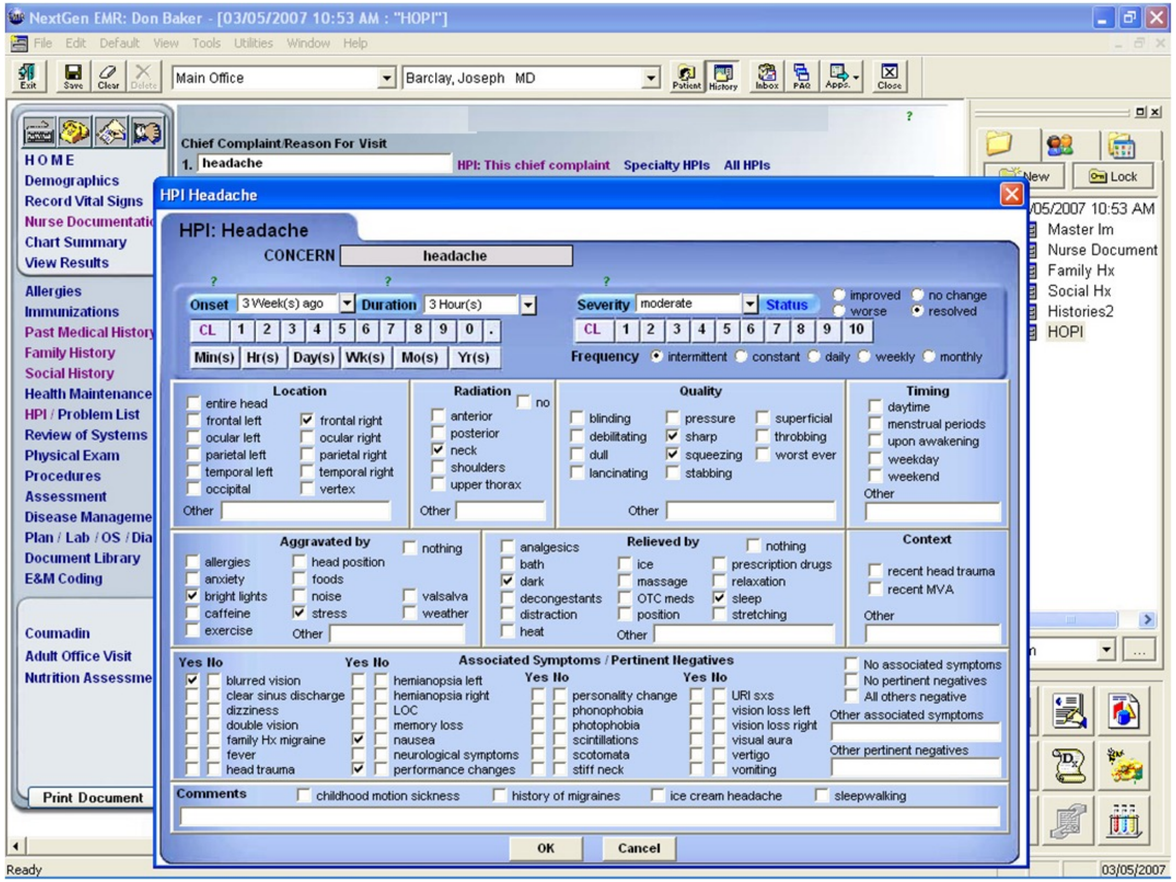
Usability evaluation



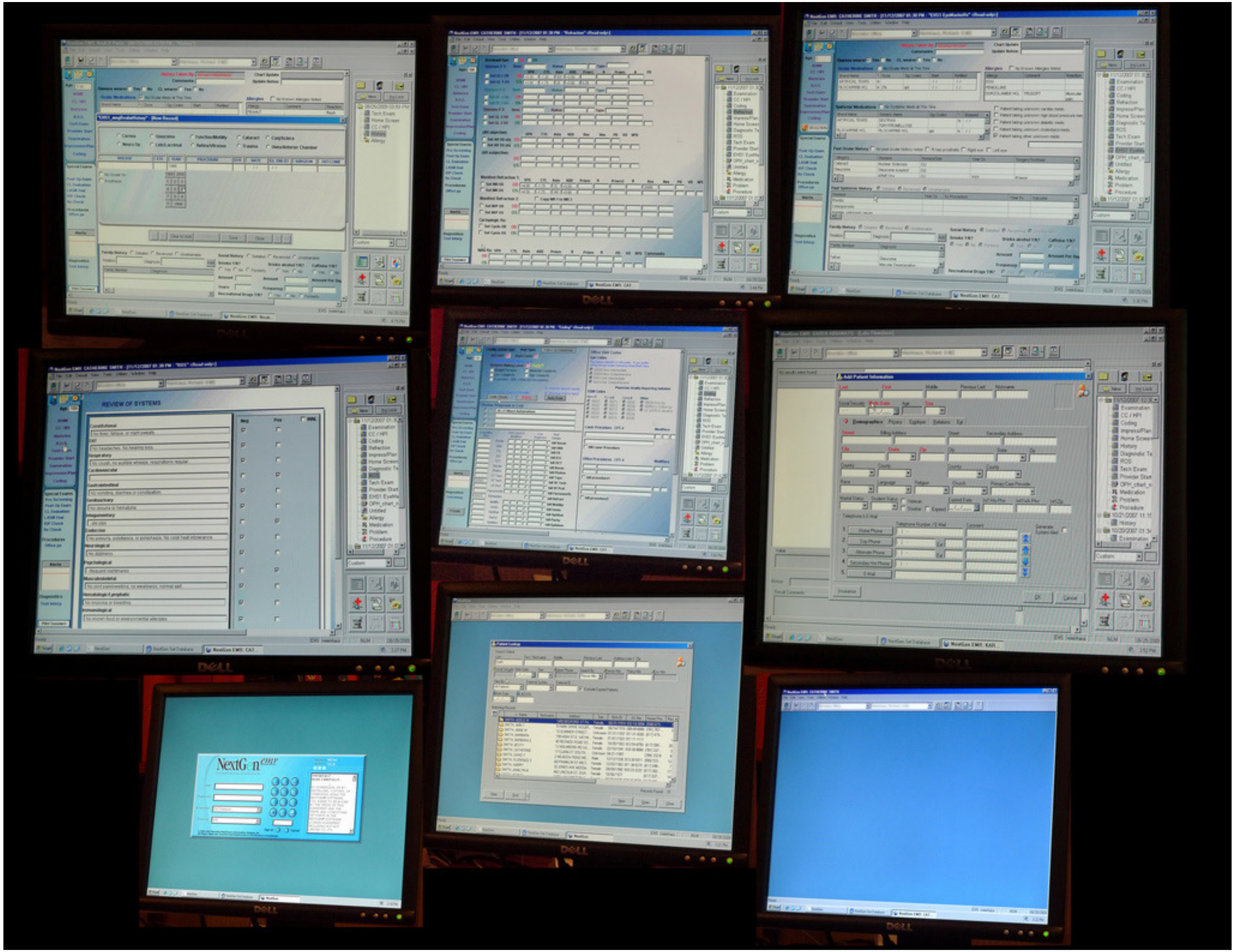
Which one is an EMR?



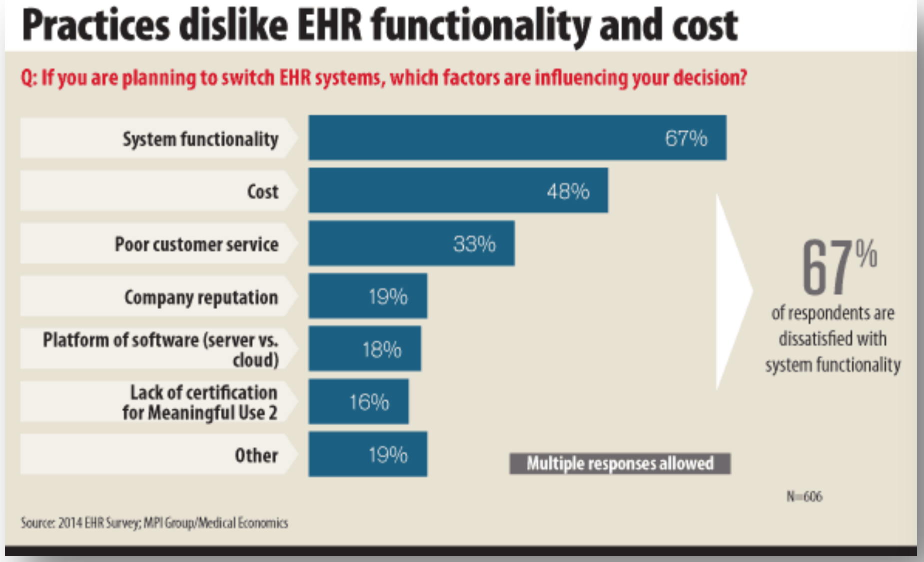
Accounting system

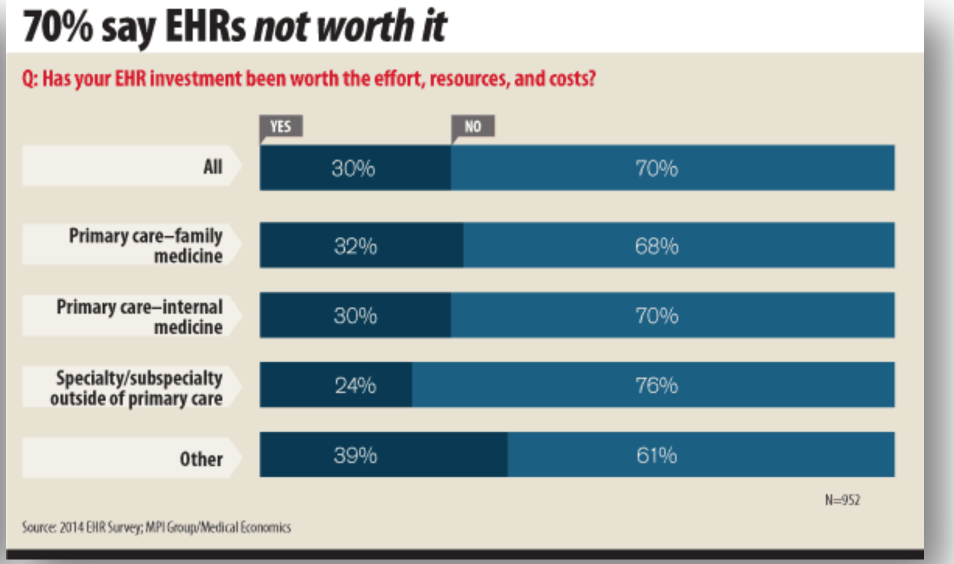


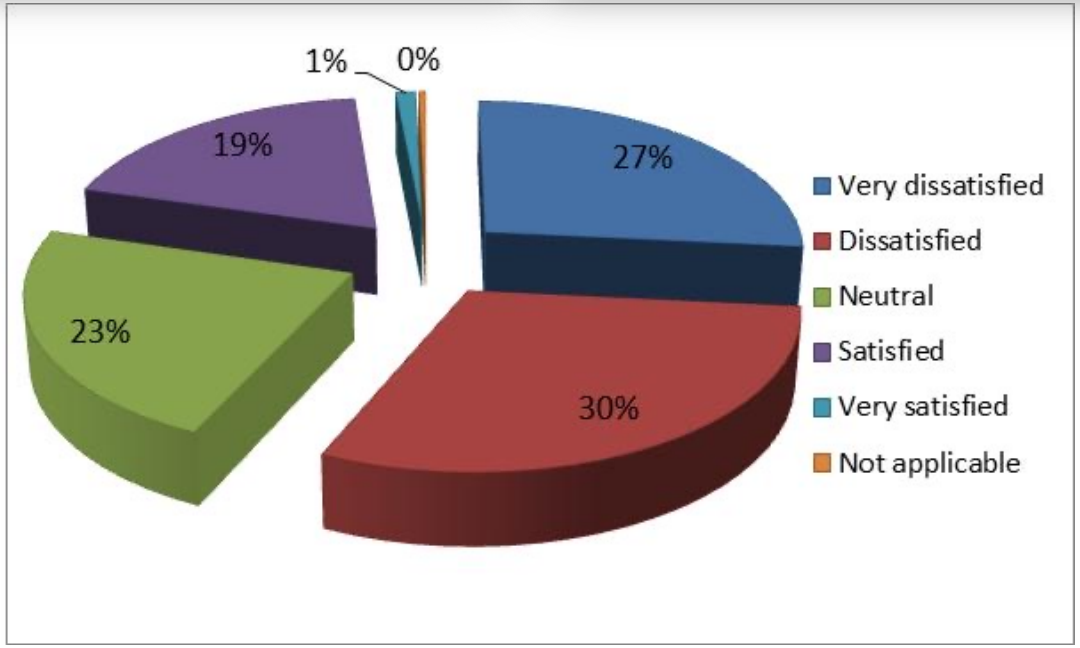
Electronic medical record


REVIEW OF SYSTEMS
NextGen emr
DELL

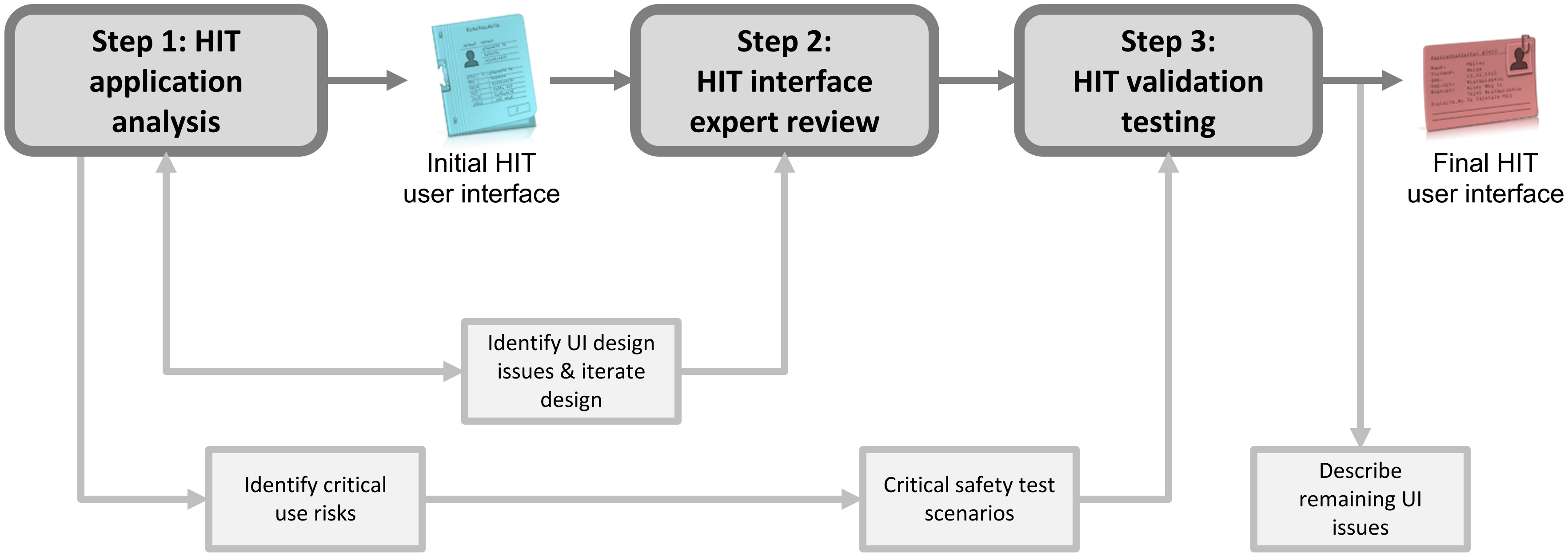
Overall satisfaction with EMR







HIT usability evaluation



Common Usability Test Methods

1. Cognitive Walk-Through
2. The keystroke-level model (KLM)
3. Heuristic Evaluation
4. The system usability scale (SUS)

Cost analysis can be applied to HIT

1. **Cost-benefit analysis (CBA):** Costs are the monetary value of changed health outcomes to produce financial gain or loss. CBA compares costs and benefits, which are quantified in common monetary units.
2. **Cost-effectiveness analysis (CEA):** The monetary cost relates to changes in an important health outcome as producing a cost-effectiveness ratio (cost-per-unit outcome). CEA compares costs in monetary units with outcomes in quantitative nonmonetary units (e.g., reduced mortality or morbidity).
3. **Cost-minimization analysis (CMA):** This analysis of technology replaces a current or alternative system and is equally effective in providing equal benefit at lower cost. In other words, CMA determines the least costly among alternative interventions that are assumed to produce equivalent outcomes.
4. **Return on investment (ROI):** This economic analysis determines the potential gain or loss from investment by simply dividing earnings by investment.

Security evaluation

1. **Administrative safeguards.** Administrative actions, policies, and procedures to protect the security, privacy, and confidentiality of patients' PHI.
2. **Physical safeguards.** Physical measures, policies, and procedures to protect workstations, IT infrastructure and equipment, and related facilities from natural hazards and unauthorized access.
3. **Technical safeguards.** Technology that protects electronic health information and controls access to it.

Case

#1 - Successful prediction model

The Stability and Workload Index for Transfer score predicts unplanned intensive care unit patient readmission: Initial development and validation*

Ognjen Gajic, MD; Michael Malinchoc, PhD; Thomas B. Comfere, MD; Marcelline R. Harris, RN, PhD; Ahmed Achouiti, MD; Murat Yilmaz, MD; Marcus J. Schultz, MD; Rolf D. Hubmayr, MD; Bekele Afessa, MD; J. Christopher Farmer, MD

Objective: Unplanned readmission of hospitalized patients to an intensive care unit (ICU) is associated with a worse outcome, but our ability to identify who is likely to deteriorate after ICU dismissal is limited. The objective of this study is to develop and validate a numerical index, named the Stability and Workload Index for Transfer, to predict ICU readmission.

Design: In this prospective cohort study, risk factors for ICU readmission were identified from a broad range of patients' admission and discharge characteristics, specific ICU interventions, and in-patient workload measurements. The prediction score was validated in two independent ICUs.

Setting: One medical and one mixed medical-surgical ICU in two tertiary centers.

Patients: Consecutive patients requiring >24 hrs of ICU care.

Interventions: None.

Measurements: Unplanned ICU readmission or unexpected death following ICU dismissal.

Results: In a derivation cohort of 1,131 medical ICU patients, 100 patients had unplanned readmissions, and five died unexpectedly in the hospital following ICU discharge. Predictors of readmission/unexpected death identified in a logistic regression analysis were ICU admission source, ICU length of stay, and day of discharge neurologic (Glasgow Coma Scale) and respiratory (hypoxemia, hypercapnia, or nursing requirements for complex respiratory care) impairment. The Stability and Workload Index for Transfer score predicted readmission more precisely (area under the curve [AUC], 0.75; 95% confidence interval [CI], 0.70–0.80) than the day of discharge Acute Physiology and Chronic Health Evaluation III score (AUC, 0.62; 95% CI, 0.56–0.68). In the two validation cohorts, the Stability and Workload Index for Transfer score predicted readmission similarly in a North American medical ICU (AUC, 0.74; 95% CI, 0.67–0.80) and a European medical-surgical ICU (AUC, 0.70; 95% CI, 0.64–0.76), but was less well calibrated in the medical-surgical ICU.

Conclusion: The Stability and Workload Index for Transfer score is derived from information readily available at the time of ICU dismissal and acceptably predicts ICU readmission. It is not known if discharge decisions based on this prediction score will decrease the number of ICU readmissions and/or improve outcome. (Crit Care Med 2008; 36:676–682)

Key Words: intensive care unit; management; organization; admission; discharge; risk; prediction score; patient readmission

Prior descriptive studies have demonstrated that critical care professionals vary decision parameters regarding who is ready to leave the unit according to workload pressure and ongoing demand for intensive care unit (ICU) beds (1–5), in part because the definitions and the determination of who is "sick" are highly variable. In fact, ICU admission and discharge criteria that are employed by individual practitioners are often subjective and may not be reproducible. Many practitioners rely on intuition and subjective clinical acumen to determine who is "ready" (as opposed to "safe") to leave the ICU. Even within the same ICU, and sometimes despite consistent nurse staffing patterns, these decision parameters can fluctuate daily (6). The impact of these inconsistencies is further magnified if insufficient numbers of qualified critical care professionals (physicians, nurses, allied health professionals) are available to provide bedside care (2). These personnel shortfalls exert powerful clinical and cost pressures on individual decision-makers, who are then forced to modulate critical care resource utilization through ICU patient triage (7).

Embedded in these transfer populations are individual patients who have a higher than recognized probability of clinical deterioration in the hours to days following ICU discharge. Published data indicate that these patients, on return to the ICU, experience a higher than predicted mortality (when adjusted for the acuity of illness and comorbidities) (8). In addition, in a busy ICU, communications

*See also p. 984.

From the Department of Internal Medicine and the Mayo Epidemiology and Translational Research in Intensive Care Program (OG, TBC, MY, RDH, BA, JCF), and the Departments of Health Sciences Research (MM, MRH) and Nursing (MRH), Mayo Clinic College of Medicine, Rochester, MN; and The Department of Intensive Care Medicine, University of Amsterdam, Amsterdam, Netherlands (AA, MJS).

Supported, in part, by National Heart, Lung, and Blood Institute grant K23 HL78743–01A1 and the Mayo Clinic.

The authors have not disclosed any potential conflicts of interest.

For information regarding this article, E-mail: gajic.ognjen@mayo.edu

DOI: 10.1097/CCM.0B013E318164E3B0

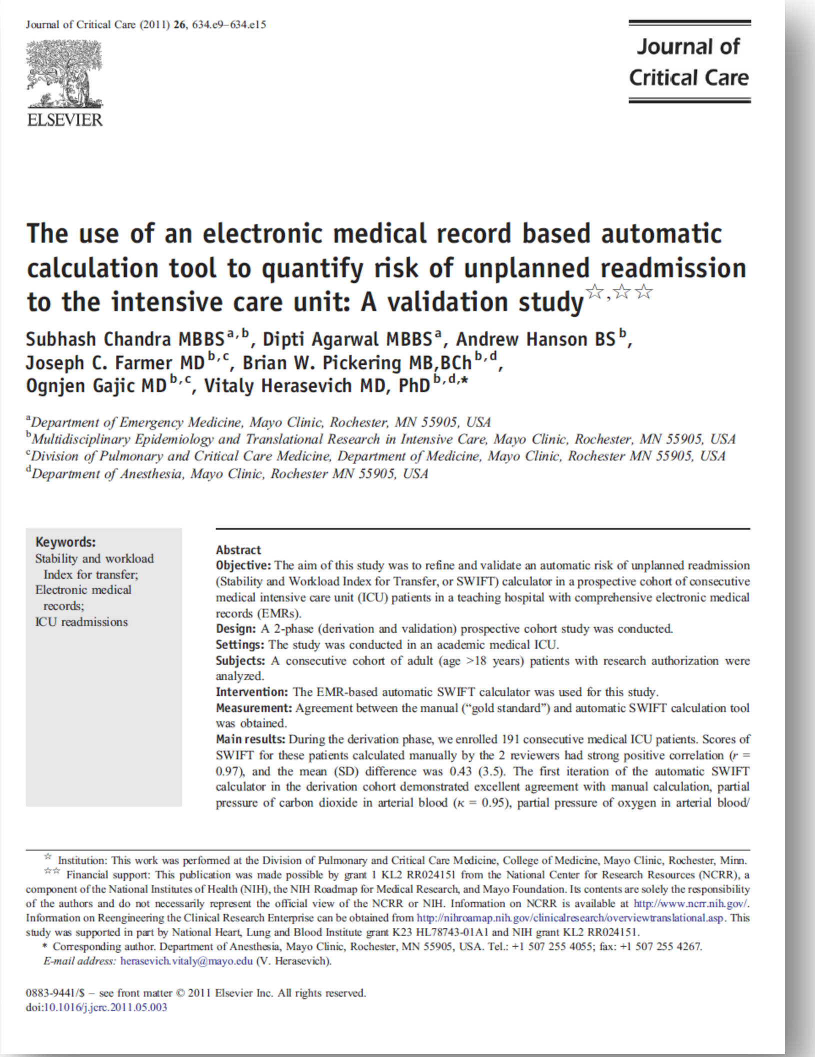
The SWIFT score predicted readmission **more precisely** (**AUC, 0.75**; 95% CI, 0.70–0.80) than the day of discharge APACHE III score (AUC, 0.62; 95% CI, 0.56–0.68).

Conclusion: The Stability and Workload Index for Transfer score is derived from information readily available at the time of ICU dismissal and <u>acceptably predicts ICU readmission.</u>

***…** It is not known if discharge decisions based on this prediction score will decrease the number of ICU readmissions and/or improve outcome.*

Gajic O, Malinchoc M, Comfere TB, et al. The Stability and Workload Index for Transfer score predicts unplanned intensive care unit patient readmission: initial development and validation. Crit Care Med 2008;36(3):676-82. PMID: 18431260

#2 - Successful electronic tool



Journal of Critical Care (2011) 26, 634.e9–634.e15

ELSEVIER

Journal of Critical Care

The use of an electronic medical record based automatic calculation tool to quantify risk of unplanned readmission to the intensive care unit: A validation study☆,☆☆

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Keywords:
Stability and workload Index for transfer;
Electronic medical records;
ICU readmissions

Abstract

Objective: The aim of this study was to refine and validate an automatic risk of unplanned readmission (Stability and Workload Index for Transfer, or SWIFT) calculator in a prospective cohort of consecutive medical intensive care unit (ICU) patients in a teaching hospital with comprehensive electronic medical records (EMRs).

Design: A 2-phase (derivation and validation) prospective cohort study was conducted.

Settings: The study was conducted in an academic medical ICU.

Subjects: A consecutive cohort of adult (age >18 years) patients with research authorization were analyzed.

Intervention: The EMR-based automatic SWIFT calculator was used for this study.

Measurement: Agreement between the manual ("gold standard") and automatic SWIFT calculation tool was obtained.

Main results: During the derivation phase, we enrolled 191 consecutive medical ICU patients. Scores of SWIFT for these patients calculated manually by the 2 reviewers had strong positive correlation (r = 0.97), and the mean (SD) difference was 0.43 (3.5). The first iteration of the automatic SWIFT calculator in the derivation cohort demonstrated excellent agreement with manual calculation, partial pressure of carbon dioxide in arterial blood (κ = 0.95), partial pressure of oxygen in arterial blood/

☆ Institution: This work was performed at the Division of Pulmonary and Critical Care Medicine, College of Medicine, Mayo Clinic, Rochester, Minn.
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E-mail address: herasevich.vitaly@mayo.edu (V. Herasevich).

doi:10.1016/j.jcrc.2011.05.003

Main results: The automatic tool retained excellent correlation with gold standard calculation for SWIFT (r = 0.92), and the mean (SD) difference was −2.2 (5.5).

Conclusion: The EMR-based automatic tool accurately calculates SWIFT score and can facilitate ICU discharge decisions without the need for manual data collection.

Chandra S, Agarwal D, Hanson A, et al. The use of an electronic medical record based automatic calculation tool to quantify risk of unplanned readmission to the intensive care unit: A validation study. J Crit Care. 2011. PMID: 21715140

#3 … No impact

ORIGINAL RESEARCH

Findings from the Implementation of a Validated Readmission Predictive Tool in the Discharge Workflow of a Medical Intensive Care Unit

Uchenna R. Ofoma[1], Subhash Chandra[2], Rahul Kashyap[3], Vitaly Herasevich[3], Adil Ahmed[4], Ognjen Gajic[4], Brian W. Pickering[3], and Christopher J. Farmer[4]

[1]Division of Critical Care Medicine, Geisinger Medical Center, Danville, Pennsylvania; [2]Department of Internal Medicine, Greater Baltimore Medical Center, Baltimore, Maryland; and [3]Department of Anesthesiology and [4]Division of Pulmonary and Critical Care Medicine, Department of Internal Medicine, Mayo Clinic, Rochester, Minnesota

Abstract

Rationale: Provider decisions about patients to be discharged from the intensive care unit (ICU) are often based on subjective intuition, sometimes leading to premature discharge and early readmission. The Stability and Work Load Index for Transfer (SWIFT) score, as a risk stratification tool, has moderate ability to predict patients at risk of ICU readmission.

Objectives: To describe findings following the incorporation of the SWIFT score into the discharge workflow of a medical ICU.

Methods: The study involved 5,293 consecutive patients discharged alive from the medical ICU of an academic medical center. The SWIFT score and associated percentage risk for readmission were incorporated into daily rounds for purpose of discharge decision-making. We measured readmission rates before and after implementation and observed changes in provider discharge decisions for individual patients after SWIFT discussions.

Measurements and Main Results: Baseline (n = 1,906) and implementation (n = 1,938) cohorts differed with respect to APACHE III scores ($P = 0.03$). In the implementation cohort, 26.2% of subjects had SWIFT scores greater than 15 and thus were predicted to have a higher risk of unplanned readmissions. In this high-risk group, 25% had SWIFT discussed in their discharge planning. There was modification of provider discharge decisions in 108 (30%) of cases in which the SWIFT was discussed. SWIFT score values above a prespecified cutoff of 15 were associated with physician tendency to prolong ICU stay or to discharge to a monitored setting ($P < 0.001$). There was no difference in 24-hour or 7-day readmission rates between the baseline and implementation cohorts (1.9 vs. 2.4%, $P = 0.24$; 6.5 vs. 7.4%, $P = 0.26$, respectively) even after adjustment for severity of illness.

Conclusions: Using the SWIFT score as an adjunct to clinical judgment, physicians modified their discharge decisions in one-third of subjects. Introducing such tools into the discharge workflow may present change management challenges that limit the evaluation of their impact on readmission rates and other relevant ICU outcomes.

Keywords: care transitions; readmissions; risk stratification; quality

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Author Contributions: V.H., A.A., O.G., B.W.P., and C.J.F. contributed to the study's conception, design, implementation and data gathering. R.K. and S.C. were responsible for data analysis and interpretation. U.R.O. and S.C. were responsible for drafting the manuscript. V.H., O.G., B.W.P., and C.J.F. critically revised the article. All eight authors assisted in the subsequent revisions and have read and approved of the final manuscript.

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This article has an online supplement, which is accessible from this issue's table of contents online at www.atsjournals.org

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DOI: 10.1513/AnnalsATS.201312-436OC
Internet address: www.atsjournals.org

Unplanned readmissions to the intensive care unit (ICU) are associated with increased length of stay, mortality, and costs (1, 2). There is growing concern that early readmissions to the ICU may indicate premature discharge from index admission. Broad guidelines have been published regarding appropriate ICU discharge (3). However, decisions about

Main results: There was no difference in 24-hour or 7-day readmission rates between the baseline and implementation cohorts (1.9 vs. 2.4%, $P = 0.24$; 6.5 vs. 7.4%, $P = 0.26$, respectively) even after adjustment for severity of illness.

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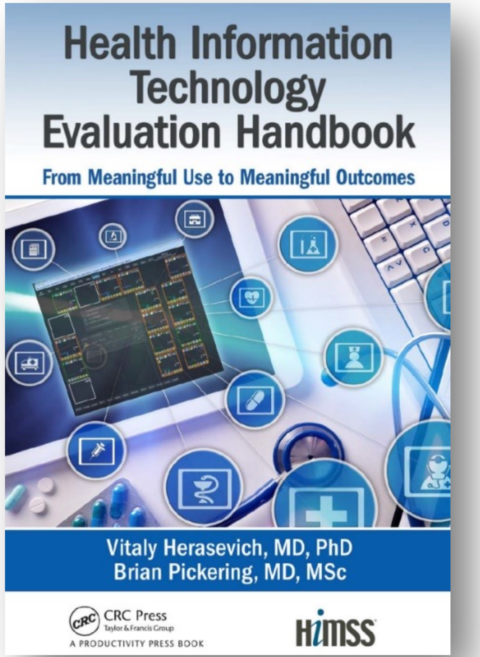
Ofoma UR, Chandra S, Kashyap R, et al. Findings from the Implementation of a Validated Readmission Predictive Tool in the Discharge Workflow of a Medical Intensive Care Unit. Ann Am Thorac Soc. 2014. PMID: 24724964)

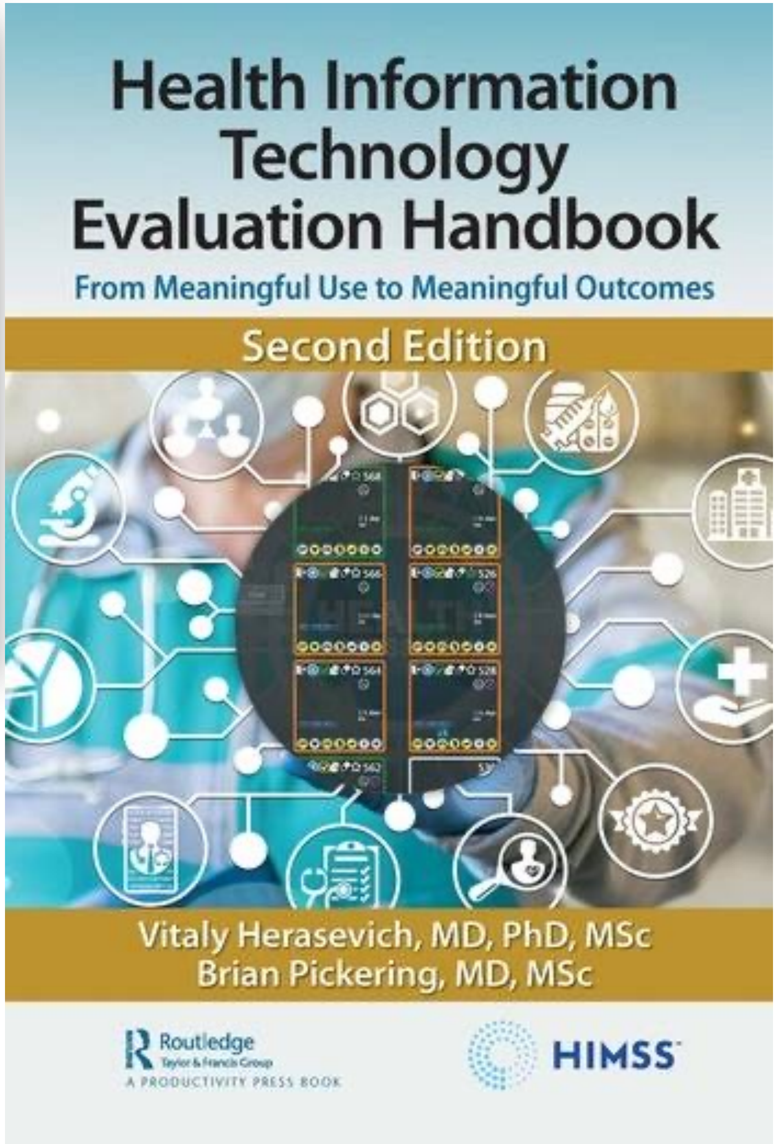
"Essentially, we're going to be moving from an electronic medical record …

which initially was just an electronic version of a paper record ...

to a smart electronic medical record that brings together what we know from research, practice and education and helps the provider provide better care"

John Noseworthy, M.D.
Mayo Clinic President and CEO
Spring 2010





Thank You!

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