TROMSØ TELEMEDICINE LABORATORY

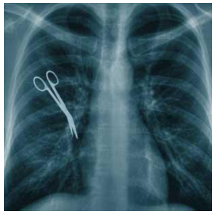
Clinical decision support (CDS) and predictive modeling for process management

Knut Magne Augestad, MD

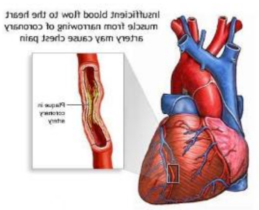
Norwegian National Center of Telemedicine and Integrated Care

CIO forum IT Helse Oslo 24 Mai

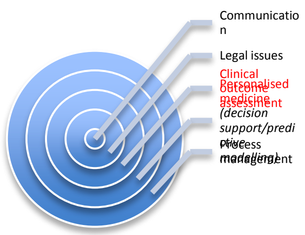
Background



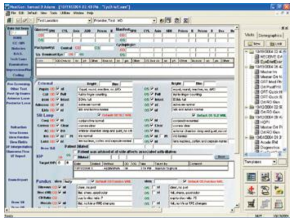
Mistakes do happen (sometimes!)



Complications do happen (often!!)

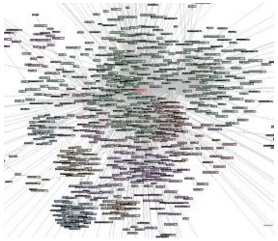


What is the purpose of the EMR ?



EMR for outcome assessment

Use the past to predict the future

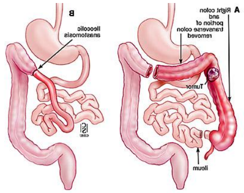


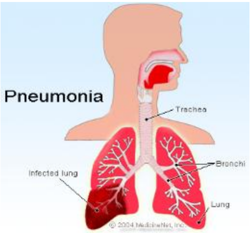
Natural Language Processing

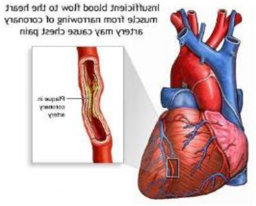
Colorectal resection has a complication rate of 20%-30%

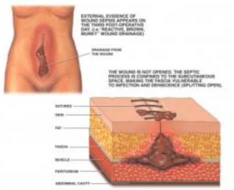
Kehlet H. Fast-track colorectal surgery. Lancet. 2008;**371:791-793.**

- Anastomosis leakage
- Pulmonary embolism
- Deep vein thrombosis
- Respiratory distress
- Pneumonia
- Myocardial infarction
- Wound infection

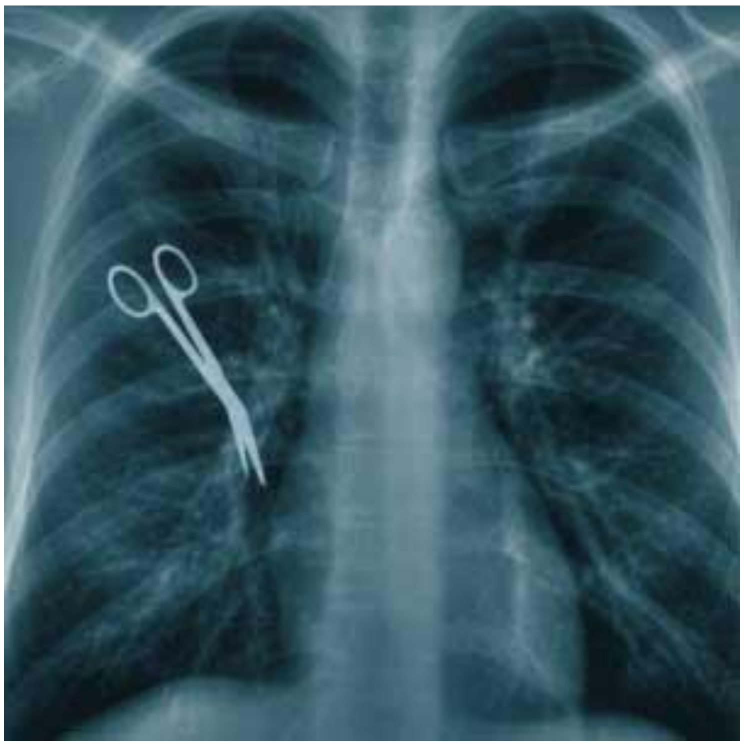








Medical errors do certainly (and unfortunately) happen…..



ORIGINAL ARTICLE

ONLINE FIRST

Incorrect Surgical Procedures Within and Outside of the Operating Room

A Follow-up Report

Julia Neily, RN, MS, MPH; Peter D. Mills, PhD, MS; Noel Eldridge, MS; Brian T. Carney, MD; Debora Pfeffer, RN, MBA; James R. Turner, BS; Yinong Young-Xu, ScD, MA, MS; William Gunnar, MD, JD; James P. Bagian, MD, PE

Objective: To describe incorrect surgical procedures reported from mid-2006 to 2009 from Veterans Health Administration medical centers and build on previously reported events from 2001 to mid-2006.

Design: Retrospective database review.

Setting: Veterans Health Administration medical centers.

Interventions: The Veterans Health Administration implemented Medical Team Training and continues to support their directive for ensuring correct surgery to improve surgical patient safety.

Main Outcome Measures: The categories were incorrect procedure types (wrong patient, side, site, procedure, or implant), major or minor surgery, in or out of the operating room (OR), adverse event or close call, specialty, and harm.

Results: Our review produced 237 reports (101 adverse events, 136 close calls) and found decreased harm compared with the previous report. The rate of reported adverse events decreased from 3.21 to 2.4 per month ($P = .02$). Reported close calls increased from 1.97 to 3.24 per month ($P \leq .001$). Adverse events were evenly split between OR (50) and non-OR (51). When in-OR events were examined as a rate, Neurosurgery had 1.56 and Ophthalmology had 1.06 reported adverse events per 10 000 cases. The most common root cause for adverse events was a lack of standardization of clinical processes (18%).

Conclusions: The rate of reported adverse events and harm decreased, while reported close calls increased. Despite improvements, we aim to achieve further gains. Current plans and actions include sharing lessons learned from root cause analyses, policy changes based on root cause analysis review, and additional focused Medical Team Training as needed.

Arch Surg. 2011;146(11):1235-1239. Published online July 18, 2011. doi:10.1001/archsurg.2011.171


...AND THAT IS WHY WE LIFT ON THREE...
COMMUNICATION
©DOLIGHAN.
dolighan.com

TROMSØ TELEMEDICINE LABORATORY

Focus on outcomes and quality do matter

- Stulberg et al
- 405 000 surgical discharges
- 600 hospitals
- Adherence to quality indicators reduces postoperative wound infections
- OR = 0.85

Adherence to Surgical Care Improvement Project Measures and the Association With Postoperative Infections

Jonah J. Stulberg, MD, PhD, MPH
Conor P. Delaney, MD, PhD
Duncan V. Neuhauser, PhD
David C. Aron, MD, MS
Pingfu Fu, PhD
Siran M. Koroukian, PhD

Context The Surgical Care Improvement Project (SCIP) aims to reduce surgical infectious complication rates through measurement and reporting of 6 infection-prevention process-of-care measures. However, an association between SCIP performance and clinical outcomes has not been demonstrated.

Objective To examine the relationship between SCIP infection-prevention process-of-care measures and postoperative infection rates.

Design, Setting, Participants A retrospective cohort study, using Premier Inc's Perspective Database for discharges between July 1, 2006 and March 31, 2008, of 405 720 patients (69% white and 11% black; 46% Medicare patients; and 68% elective surgical cases) from 398 hospitals in the United States for whom SCIP performance was recorded and submitted for public report on the Hospital Compare Web site. Three original infection-prevention measures (S-INF-Core) and all 6 infection-prevention measures (S-INF) were aggregated into 2 separate all-or-none composite scores. Hierarchical logistical models were used to assess process-of-care relationships at the patient level while accounting for hospital characteristics.

Main Outcome Measure The ability of reported adherence to SCIP infection-prevention process-of-care measures (using the 2 composite scores of S-INF and S-INF-Core) to predict postoperative infections.

Results There were 3996 documented postoperative infections. The S-INF composite process-of-care measure predicted a decrease in postoperative infection rates from 14.2 to 6.8 per 1000 discharges (adjusted odds ratio, 0.85; 95% confidence interval, 0.76-0.95). The S-INF-Core composite process-of-care measure predicted a decrease in postoperative infection rates from 11.5 to 5.3 per 1000 discharges (adjusted odds ratio, 0.86; 95% confidence interval, 0.74-1.01), which was not a statistically significantly lower probability of infection. None of the individual SCIP measures were significantly associated with a lower probability of infection.

Conclusions Among hospitals in the Premier Inc Perspective Database reporting SCIP performance, adherence measured through a global all-or-none composite infection-prevention score was associated with a lower probability of developing a postoperative infection. However, adherence reported on individual SCIP measures, which is the only form in which performance is publicly reported, was not associated with a significantly lower probability of infection.

JAMA. 2010;303(24):2479-2485 www.jama.com

The Surgical Care Improvement Project (SCIP), a national quality partnership dedicated to reducing the rate of surgical complications, has developed 20 measures covering various discrete elements of patient care.[1,2] There are 9 publicly reported SCIP measures, 6 of which focus on postoperative infection prevention (Box). Adoption of these measures was supported by research attesting to their efficacy; and the development and implementation of these process-of-care measures has been endorsed by the National Quality Forum and other organizations that promote improvements in the quality of medical care.[1-3]

Hospital participation in these data collection efforts is voluntary. However, the Centers for Medicare & Medicaid Services (CMS) reduces hospital reimbursement by 2% if they fail to report their performance on these measures.[4-7] After validation and cleanup

Outcome research in medicine is challenging because there exists wide variation in practice

- Wide international variations in cancer management.

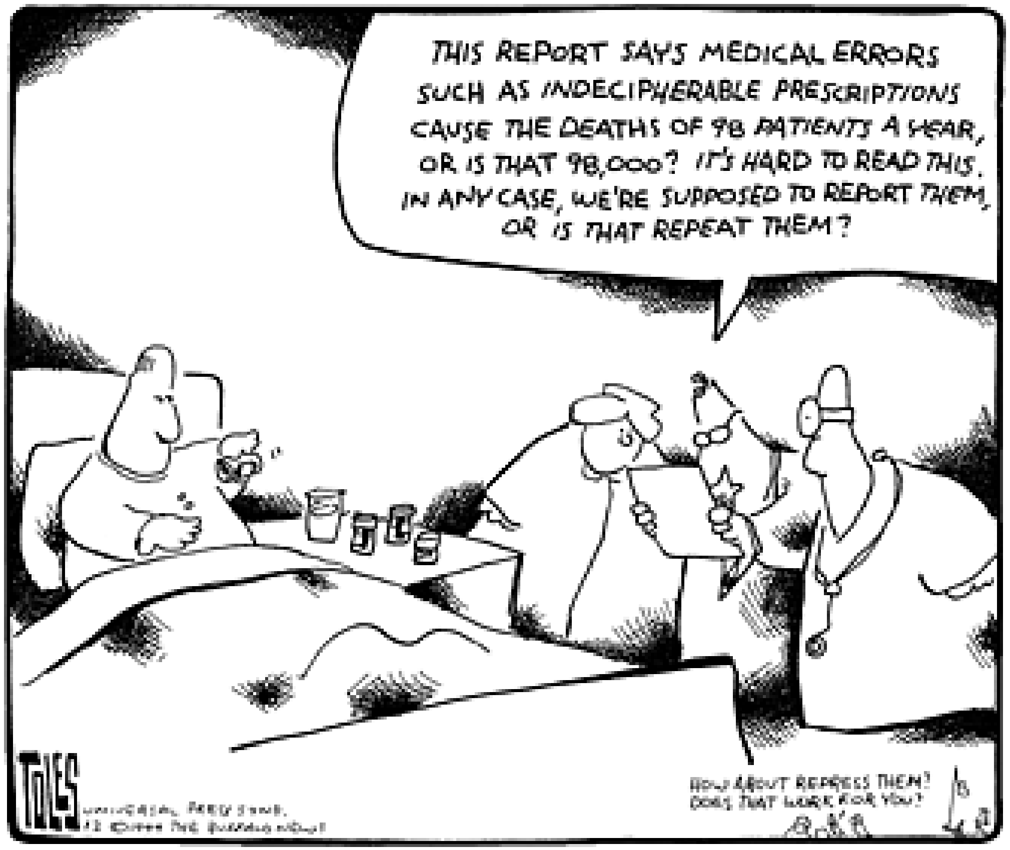
  Augestad, K. M., Lindsetmo,, et al. (2011). International trends in surgical treatment of rectal cancer. American Journal of Surgery

- Influence on health care costs, side effects and survival.

  Augestad, K. M., Lindsetmo et al. (2011). Preoperative Rectal Cancer Management: Wide International Practice Makes Outcome Comparison Challenging. World Journal of Surgery.

- New bio statistical methods needed

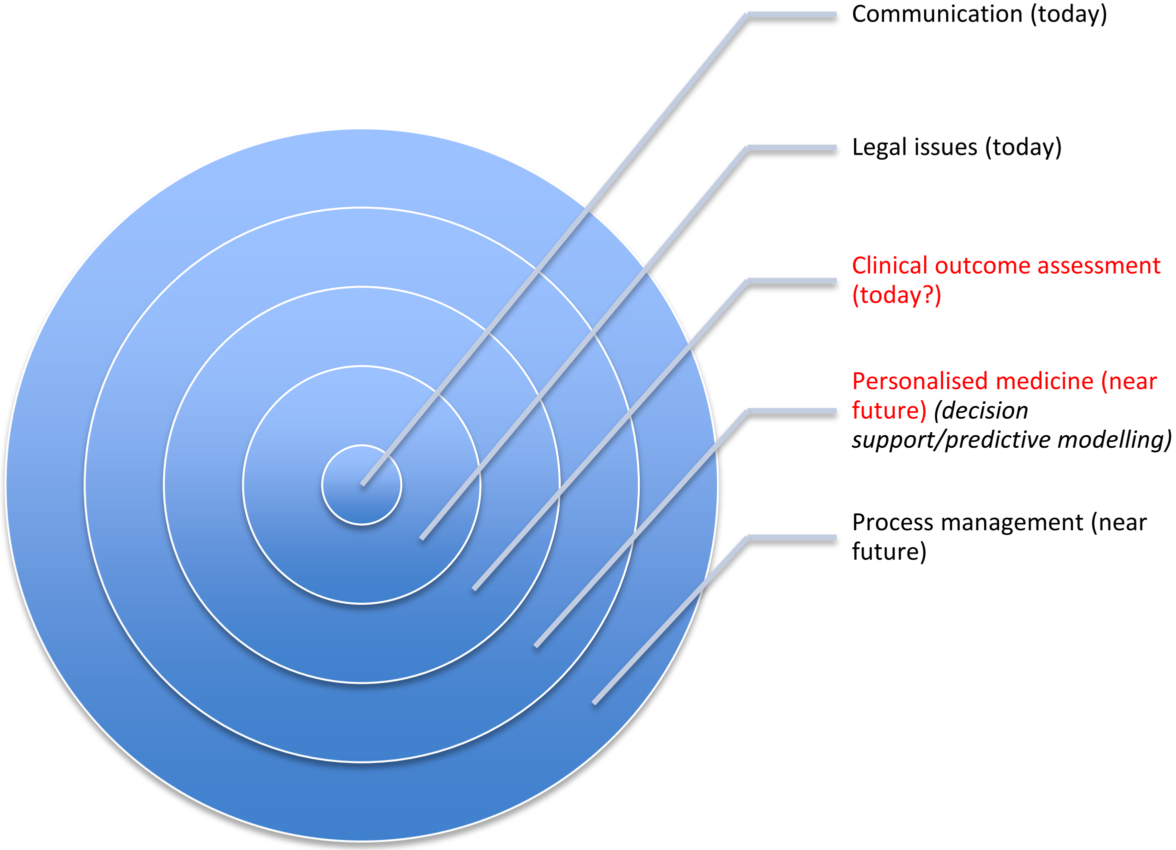
  Haut, E. R. (2010). Are surgeons ready to embrace a paradigm shift in surgical comparative effectiveness research. Archives of Surgery.


THIS REPORT SAYS MEDICAL ERRORS SUCH AS INDECIPHERABLE PRESCRIPTIONS CAUSE THE DEATHS OF 98 PATIENTS A YEAR, OR IS THAT 98,000? IT'S HARD TO READ THIS. IN ANY CASE, WE'RE SUPPOSED TO REPORT THEM, OR IS THAT REPEAT THEM?
HOW ABOUT REPRESS THEM? DOES THAT WORK FOR YOU?

TROMSØ TELEMEDICINE LABORATORY

UNIVERSITETET I TROMSØ

The EMR serves several different purposes



TROMSØ
TELEMEDICINE
LABORATORY

Definition of clinical decision support:

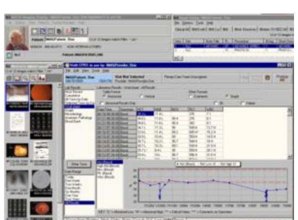
Kawamoto BMJ 2005: ”any electronic or non-electronic system designed to aid directly in clinical decision making, in which characteristics of individual patients are used to generate patient-specific assessments or recommendations that are then presented to clinicians for consideration”

CDS-factors associated with improved clinical practice

Automatic provision

At time and location

Clear recommendation



Integrated in EMR

Table 6 Features of clinical decision support systems (CDSS) associated with improved clinical practice. Results of meta-regression analyses of 71 control-CDSS comparisons

Feature*	Adjusted odds ratio (95% CI)	P value
Primary analysis (all CDSS, n=71)		
Automatic provision of decision support as part of clinician workflow	112.1 (12.9 to ∞)	<0.00001
Provision of decision support at time and location of decision making	15.4 (1.3 to 300.6)	0.0263
Provision of recommendation rather than just an assessment	7.1 (1.3 to 45.6)	0.0187
Computer based generation of decision support	6.3 (1.2 to 45.0)	0.0294
Secondary analysis (computer based CDSS, n=49)†‡		
Automatic provision of decision support as part of clinician workflow	105.0 (10.4 to ∞)	0.00001
Secondary analysis (non-electronic CDSS, n=22)†§		
Provision of recommendation rather than just an assessment	19.4 (1.5 to 1263.0)	0.0164

CDS effects

- Improve patient outcome
- Improve prescribing practice
- Reduse errors
- Enhance guideline adherence
- Enhance delivery of preventive care
- Lasting improvement clinical practice

Augestad, K. M., Berntsen, G., Lassen, K., Bellika, J. G., Wootton, R., Lindsetmo, R. O., Study Group of Research Quality in Medical Informatics and Decision Support (SQUID). (2012). Standards for reporting randomized controlled trials in medical informatics: a systematic review of CONSORT adherence in RCTs on clinical decision support. *Journal of the American Medical Informatics Association : JAMIA.*

TROMSØ TELEMEDICINE LABORATORY

UNIVERSITETET I TROMSØ

Personalized medicine is ready for the intelligent EMR

CHEST

Original Research

CRITICAL CARE

Development and Validation of a Risk Calculator Predicting Postoperative Respiratory Failure

Himani Gupta, MD; Prateek K. Gupta, MD; Xiang Fang, PhD; Weldon J. Miller, MS; Samuel Cemaj, MD; R. Armour Forse, MD, PhD; and Lee E. Morrow, MD, FCCP

Background: Postoperative respiratory failure (PRF) (requiring mechanical ventilation >48 h after surgery or unplanned intubation within 30 days of surgery) is associated with significant morbidity and mortality. The objective of this study was to identify preoperative factors associated with an increased risk of PRF and subsequently develop and validate a risk calculator.
Methods: The American College of Surgeons National Surgical Quality Improvement Program (NSQIP), a multicenter, prospective data set (2007-2008), was used. The 2007 data set (n = 211,410) served as the training set and the 2008 data set (n = 257,385) as the validation set.
Results: In the training set, 6,531 patients (3.1%) developed PRF. Patients who developed PRF had a significantly higher 30-day mortality (25.62% vs 0.98%, $P < .0001$). On multivariate logistic regression analysis, five preoperative predictors of PRF were identified: type of surgery, emergency case, dependent functional status, preoperative sepsis, and higher American Society of Anesthesiologists (ASA) class. The risk model based on the training data set was subsequently validated on the validation data set. The model performance was very similar between the training and the validation data sets (c-statistic, 0.894 and 0.897, respectively). The high c-statistics (area under the receiver operating characteristic curve) indicate excellent predictive performance. The risk model was used to develop an interactive risk calculator.
Conclusions: Preoperative variables associated with increased risk of PRF include type of surgery, emergency case, dependent functional status, sepsis, and higher ASA class. The validated risk calculator provides a risk estimate of PRF and is anticipated to aid in surgical decision making and informed patient consent.

CHEST 2011; 140(5):1207–1215

Personalized medicine is ready for the intelligent EMR

Constipation	Diarrhoea	Rectal bleeding	Loss of Weight	Abdominal pain	Abdominal tenderness	Abnormal rectal exam	Haemoglobin 10–13 g dl^{-1}	Haemoglobin <10 g dl^{-1}	
0.42 0.3, 0.5	0.94 0.7, 1.1	2.4 1.9, 3.2	1.2 0.9, 1.6	1.1 0.9, 1.3	1.1 0.8, 1.5	1.5 1.0, 2.2	0.97 0.8, 1.3	2.3 1.6, 3.1	PPV as a single symptom
0.81 0.5, 1.3	1.1 0.6, 1.8	2.4 1.4, 4.4	3.0 1.7, 5.4	1.5 1.0, 2.2	1.7 0.9, 3.4	2.6	1.2 0.6, 2.7	2.6	Constipation
	1.5 1.0, 2.2	3.4 2.1, 6.0	3.1 1.8, 5.5	1.9 1.4, 2.7	2.4 1.3, 4.8	11	2.2 1.2, 4.3	2.9	Diarrhoea
		6.8	4.7	3.1 1.9, 5.3	4.5	8.5	3.6	3.2	Rectal bleeding
			1.4 0.8, 2.6	3.4 2.1, 6.0	6.4	7.4	1.3 0.7, 2.6	4.7	Loss of weight
				3.0 1.8, 5.2	1.4 0.3, 2.2	3.3	2.2 1.1, 4.5	6.9	Abdominal pain
					1.7 0.8, 3.7	5.8	2.7	>10	Abdominal tenderness

Hamilton, W., Round, A., Sharp, D., & Peters, T. J. (2005). Clinical features of colorectal cancer before diagnosis: a population-based case–control study. British Journal of Cancer, 93(4), 399–405.

TROMSØ TELEMEDICINE LABORATORY

Personalized medicine is ready for the intelligent EMR

JOURNAL OF CLINICAL ONCOLOGY | ORIGINAL REPORT

Predicting Survival After Curative Colectomy for Cancer: Individualizing Colon Cancer Staging

Martin R. Weiser, Mithat Gönen, Joanne F. Chou, Michael W. Kattan, and Deborah Schrag

Martin R. Weiser, Mithat Gönen, Joanne F. Chou, and Deborah Schrag, Memorial Sloan-Kettering Cancer Center, New York, NY; Michael W. Kattan, Cleveland Clinic, Cleveland, OH; and Deborah Schrag, Dana-Farber Cancer Center, Boston, MA.

Submitted April 11, 2011; accepted September 14, 2011; published online ahead of print at www.jco.org on November 14, 2011.

Supported in part by a grant from the American Joint Committee on Cancer (M.R.W.) and a grant from the Society of Memorial Sloan-Kettering Cancer Center (M.R.W.).

Authors' disclosures of potential conflicts of interest and author contributions are found at the end of this article.

Corresponding author: Martin R. Weiser, MD, Colorectal Service/Department of Surgery, Memorial Sloan-Kettering Cancer Center, 1275 York Ave, Room C-1075, New York, NY 10065; e-mail: weiser1@mskcc.org.

0732-183X/11/2999-1/$20.00

DOI: 10.1200/JCO.2011.36.5080

A B S T R A C T

Purpose
Cancer staging determines extent of disease, facilitating prognostication and treatment decision making. The American Joint Committee on Cancer (AJCC) TNM classification system is the most commonly used staging algorithm for colon cancer, categorizing patients on the basis of only these three variables (tumor, node, and metastasis). The purpose of this study was to extend the seventh edition of the AJCC staging system for colon cancer to incorporate additional information available from tumor registries, thereby improving prognostic accuracy.

Methods
Records from 128,853 patients with primary colon cancer reported to the Surveillance, Epidemiology and End Results Program from 1994 to 2005 were used to construct and validate three survival models for patients with primary curative-intent surgery. Independent training/test data sets were used to develop and test alternative models. The seventh edition TNM staging system was compared with models supplementing TNM staging with additional demographic and tumor variables available from the registry by calculating a concordance index, performing calibration, and identifying the area under receiver operating characteristic (ROC) curves.

Results
Inclusion of additional registry covariates improved prognostic estimates. The concordance index rose from 0.60 (95% CI, 0.59 to 0.61) for the AJCC model, with T- and N-stage variables, to 0.68 (95% CI, 0.67 to 0.68) for the model including tumor grade, number of collected metastatic lymph nodes, age, and sex. ROC curves for the extended model had higher sensitivity, at all values of specificity, than the TNM system; calibration curves indicated no deviation from the reference line.

Conclusion
Prognostic models incorporating readily available data elements outperform the current AJCC system. These models can assist in personalizing treatment and follow-up for patients with colon cancer.

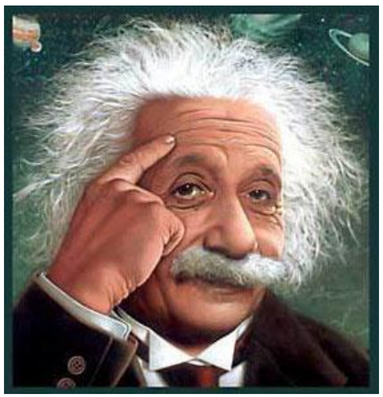
J Clin Oncol 29. © 2011 by American Society of Clinical Oncology

Predictive modelling

TROMSØ
TELEMEDICINE
LABORATORY

Outcome assessment: Times they are changing……

Registries

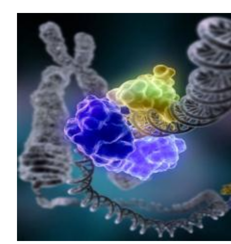


Intelligent EMR

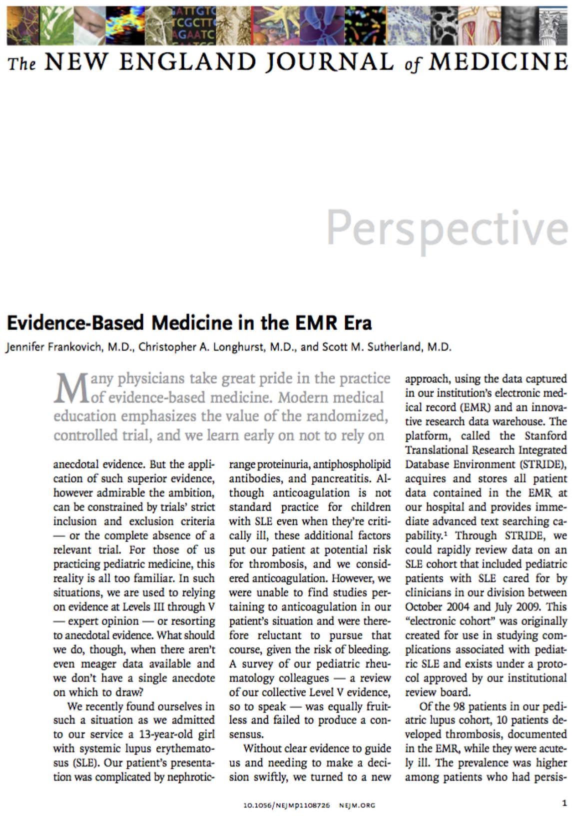
Personalised
medicine

Statistical
modelling

EMR data



Autumn 2011 two of the big five discuss analyses of EMR data



The NEW ENGLAND JOURNAL of MEDICINE

Perspective

Evidence-Based Medicine in the EMR Era

Jennifer Frankovich, M.D., Christopher A. Longhurst, M.D., and Scott M. Sutherland, M.D.

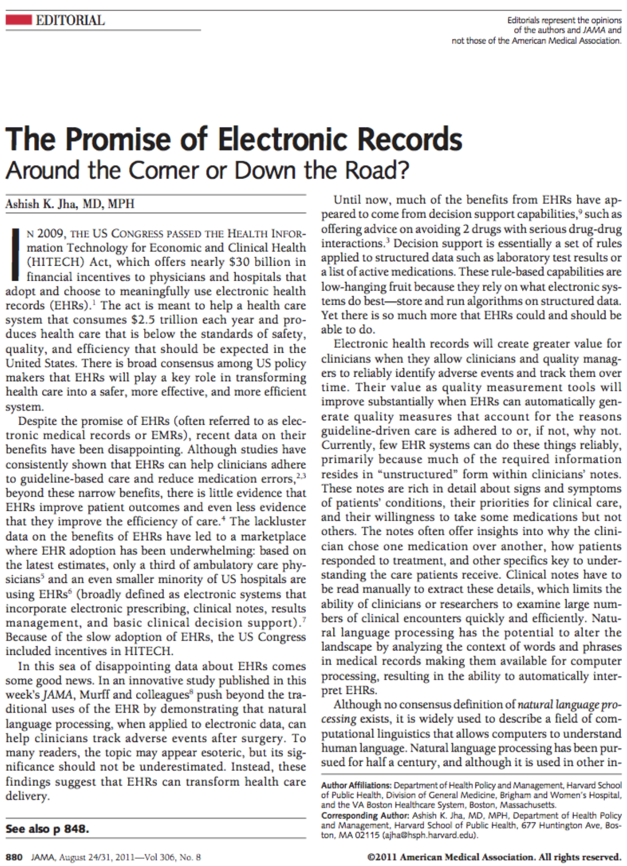
Many physicians take great pride in the practice of evidence-based medicine. Modern medical education emphasizes the value of the randomized, controlled trial, and we learn early on not to rely on anecdotal evidence. But the application of such superior evidence, however admirable the ambition, can be constrained by trials' strict inclusion and exclusion criteria — or the complete absence of a relevant trial. For those of us practicing pediatric medicine, this reality is all too familiar. In such situations, we are used to relying on evidence at Levels III through V — expert opinion — or resorting to anecdotal evidence. What should we do, though, when there aren't even meager data available and we don't have a single anecdote on which to draw?

We recently found ourselves in such a situation as we admitted to our service a 13-year-old girl with systemic lupus erythematosus (SLE). Our patient's presentation was complicated by nephrotic-range proteinuria, antiphospholipid antibodies, and pancreatitis. Although anticoagulation is not standard practice for children with SLE even when they're critically ill, these additional factors put our patient at potential risk for thrombosis, and we considered anticoagulation. However, we were unable to find studies pertaining to anticoagulation in our patient's situation and were therefore reluctant to pursue that course, given the risk of bleeding. A survey of our pediatric rheumatology colleagues — a review of our collective Level V evidence, so to speak — was equally fruitless and failed to produce a consensus.

Without clear evidence to guide us and needing to make a decision swiftly, we turned to a new approach, using the data captured in our institution's electronic medical record (EMR) and an innovative research data warehouse. The platform, called the Stanford Translational Research Integrated Database Environment (STRIDE), acquires and stores all patient data contained in the EMR at our hospital and provides immediate advanced text searching capability.[1] Through STRIDE, we could rapidly review data on an SLE cohort that included pediatric patients with SLE cared for by clinicians in our division between October 2004 and July 2009. This "electronic cohort" was originally created for use in studying complications associated with pediatric SLE and exists under a protocol approved by our institutional review board.

Of the 98 patients in our pediatric lupus cohort, 10 patients developed thrombosis, documented in the EMR, while they were acutely ill. The prevalence was higher among patients who had persis-

10.1056/NEJMp1108726 NEJM.ORG



EDITORIAL

Editorials represent the opinions of the authors and *JAMA* and not those of the American Medical Association.

The Promise of Electronic Records
Around the Corner or Down the Road?

Ashish K. Jha, MD, MPH

In 2009, the US Congress passed the Health Information Technology for Economic and Clinical Health (HITECH) Act, which offers nearly $30 billion in financial incentives to physicians and hospitals that adopt and choose to meaningfully use electronic health records (EHRs).[1] The act is meant to help a health care system that consumes $2.5 trillion each year and produces health care that is below the standards of safety, quality, and efficiency that should be expected in the United States. There is broad consensus among US policy makers that EHRs will play a key role in transforming health care into a safer, more effective, and more efficient system.

Despite the promise of EHRs (often referred to as electronic medical records or EMRs), recent data on their benefits have been disappointing. Although studies have consistently shown that EHRs can help clinicians adhere to guideline-based care and reduce medication errors,[2,3] beyond these narrow benefits, there is little evidence that EHRs improve patient outcomes and even less evidence that they improve the efficiency of care.[4] The lackluster data on the benefits of EHRs have led to a marketplace where EHR adoption has been underwhelming: based on the latest estimates, only a third of ambulatory care physicians[5] and an even smaller minority of US hospitals are using EHRs[6] (broadly defined as electronic systems that incorporate electronic prescribing, clinical notes, results management, and basic clinical decision support).[7] Because of the slow adoption of EHRs, the US Congress included incentives in HITECH.

In this sea of disappointing data about EHRs comes some good news. In an innovative study published in this week's *JAMA*, Murff and colleagues[8] push beyond the traditional uses of the EHR by demonstrating that natural language processing, when applied to electronic data, can help clinicians track adverse events after surgery. To many readers, the topic may appear esoteric, but its significance should not be underestimated. Instead, these findings suggest that EHRs can transform health care delivery.

See also p 848.

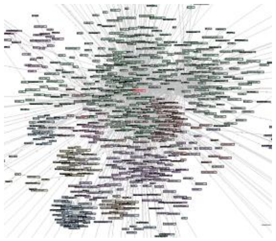
Until now, much of the benefits from EHRs have appeared to come from decision support capabilities,[9] such as offering advice on avoiding 2 drugs with serious drug-drug interactions.[3] Decision support is essentially a set of rules applied to structured data such as laboratory test results or a list of active medications. These rule-based capabilities are low-hanging fruit because they rely on what electronic systems do best—store and run algorithms on structured data. Yet there is so much more that EHRs could and should be able to do.

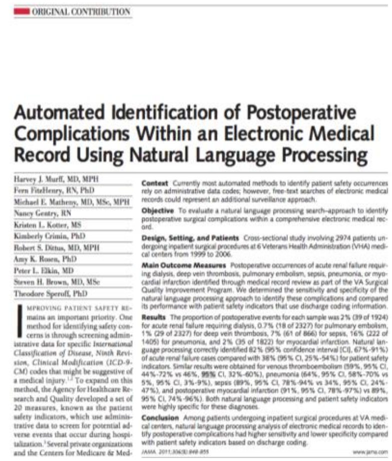
Electronic health records will create greater value for clinicians when they allow clinicians and quality managers to reliably identify adverse events and track them over time. Their value as quality measurement tools will improve substantially when EHRs can automatically generate quality measures that account for the reasons guideline-driven care is adhered to or, if not, why not. Currently, few EHR systems can do these things reliably, primarily because much of the required information resides in "unstructured" form within clinicians' notes. These notes are rich in detail about signs and symptoms of patients' conditions, their priorities for clinical care, and their willingness to take some medications but not others. The notes often offer insights into why the clinician chose one medication over another, how patients responded to treatment, and other specifics key to understanding the care patients receive. Clinical notes have to be read manually to extract these details, which limits the ability of clinicians or researchers to examine large numbers of clinical encounters quickly and efficiently. Natural language processing has the potential to alter the landscape by analyzing the context of words and phrases in medical records making them available for computer processing, resulting in the ability to automatically interpret EHRs.

Although no consensus definition of *natural language processing* exists, it is widely used to describe a field of computational linguistics that allows computers to understand human language. Natural language processing has been pursued for half a century, and although it is used in other in-

Author Affiliations: Department of Health Policy and Management, Harvard School of Public Health, Division of General Medicine, Brigham and Women's Hospital, and the VA Boston Healthcare System, Boston, Massachusetts.
Corresponding Author: Ashish K. Jha, MD, MPH, Department of Health Policy and Management, Harvard School of Public Health, 677 Huntington Ave, Boston, MA 02115 (ajha@hsph.harvard.edu).

Natural Language Processing has higher sensitivity in EMR outcome assessment compared to ICD-9





ORIGINAL CONTRIBUTION

Automated Identification of Postoperative Complications Within an Electronic Medical Record Using Natural Language Processing

Harvey J. Murff, MD, MPH
Fern FitzHenry, RN, PhD
Michael E. Matheny, MD, MSc, MPH
Nancy Gentry, RN
Kristen L. Kotter, MS
Kimberly Crimin, PhD
Robert S. Dittus, MD, MPH
Amy K. Rosen, PhD
Peter L. Elkin, MD
Steven H. Brown, MD, MSc
Theodore Speroff, PhD

Context Currently most automated methods to identify patient safety occurrences rely on administrative data codes; however, free-text searches of electronic medical records could represent an additional surveillance approach.

Objective To evaluate a natural language processing search–approach to identify postoperative surgical complications within a comprehensive electronic medical record.

Design, Setting, and Patients Cross-sectional study involving 2974 patients undergoing inpatient surgical procedures at 6 Veterans Health Administration (VHA) medical centers from 1999 to 2006.

Main Outcome Measures Postoperative occurrences of acute renal failure requiring dialysis, deep vein thrombosis, pulmonary embolism, sepsis, pneumonia, or myocardial infarction identified through medical record review as part of the VA Surgical Quality Improvement Program. We determined the sensitivity and specificity of the natural language processing approach to identify these complications and compared its performance with patient safety indicators that use discharge coding information.

Results The proportion of postoperative events for each sample was 2% (39 of 1924) for acute renal failure requiring dialysis, 0.7% (18 of 2327) for pulmonary embolism, 1% (29 of 2327) for deep vein thrombosis, 7% (61 of 866) for sepsis, 16% (222 of 1405) for pneumonia, and 2% (35 of 1822) for myocardial infarction. Natural language processing correctly identified 82% (95% confidence interval [CI], 67%-91%) of acute renal failure cases compared with 38% (95% CI, 25%-54%) for patient safety indicators. Similar results were obtained for venous thromboembolism (59%, 95% CI, 44%-72% vs 46%, 95% CI, 32%-60%), pneumonia (64%, 95% CI, 58%-70% vs 5%, 95% CI, 3%-9%), sepsis (89%, 95% CI, 78%-94% vs 34%, 95% CI, 24%-47%), and postoperative myocardial infarction (91%, 95% CI, 78%-97%) vs 89%, 95% CI, 74%-96%). Both natural language processing and patient safety indicators were highly specific for these diagnoses.

Conclusion Among patients undergoing inpatient surgical procedures at VA medical centers, natural language processing analysis of electronic medical records to identify postoperative complications had higher sensitivity and lower specificity compared with patient safety indicators based on discharge coding.

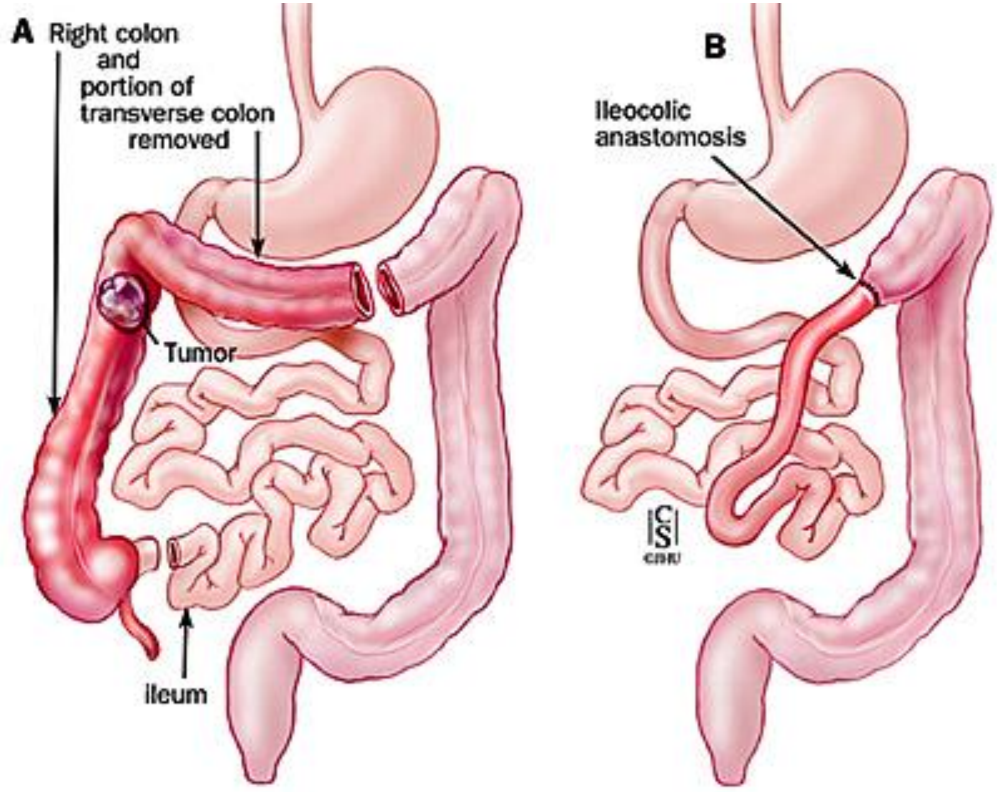
JAMA. 2011;306(8):848-855 www.jama.com

IMPROVING PATIENT SAFETY REmains an important priority. One method for identifying safety concerns is through screening administrative data for specific *International Classification of Disease, Ninth Revision, Clinical Modification* (*ICD-9-CM*) codes that might be suggestive of a medical injury.[1,2] To expand on this method, the Agency for Healthcare Research and Quality developed a set of 20 measures, known as the patient safety indicators, which use administrative data to screen for potential adverse events that occur during hospitalization.[3] Several private organizations and the Centers for Medicare & Med-

Table 3. Comparison of a Natural Language Processing–Based Approach to the Agency for Healthcare Research and Quality Patient Safety Indicators in Identifying Postoperative Complications

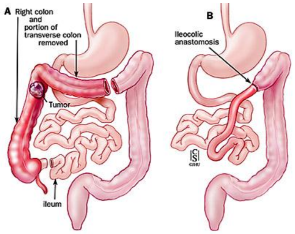
Occurrence	Event Rate	Test Characteristic	Natural Language Processing	Patient Safety Indicator	*P* Value
Acute renal failure	39/1924	Sensitivity	0.82 (0.67-0.91)	0.38 (0.25-0.54)	<.001
		Specificity	0.94 (0.93-0.95)	1.00 (1.00-1.00)	<.001
Pulmonary embolism/ deep vein thrombosis	46/2327	Sensitivity	0.59 (0.44-0.72)	0.46 (0.32-0.60)	.30
		Specificity	0.91 (0.90-0.92)	0.98 (0.98-0.99)	<.001
Sepsis	61/866	Sensitivity	0.89 (0.78-0.94)	0.34 (0.24-0.47)	<.001
		Specificity	0.94 (0.93-0.96)	0.99 (0.98-0.99)	<.001
Pneumonia	222/1405	Sensitivity	0.64 (0.58-0.70)	0.05 (0.03-0.09)	<.001
		Specificity	0.95 (0.94-0.96)	0.99 (0.99-1.00)	<.001
Myocardial infarction	35/1822	Sensitivity	0.91 (0.78-0.97)	0.89 (0.74-0.96)	.67
		Specificity	0.95 (0.94-0.96)	0.99 (0.98-0.99)	<.001

Anastomosis leakage is a common complication in GI surgery



In my own department we observed a 25% reduction in anastomosis leakage

	2006	2007	2008	2009	2010
Number of procedures	84	80	87	91	91
% anastomotic leak rate	11	31	17	15	5



EMR identification of anastomoses leakage equals a combination of different types of data

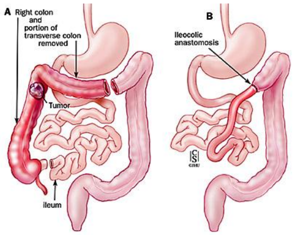
Blood samples
- CRP value > X
- White cell blood count > X

Semantic analyses
- Text: "mavesmerter” (abdominal pain)
- Text: "sepsis"
- Text radiology: "kontrastlekkasje” (contrast leakage)

Date
- Date: > postoperative day three

Codes
- ICD 10
- Surgical procedure codes

Result
- Anastomosis leak liklelihood score high



Predictive modelling

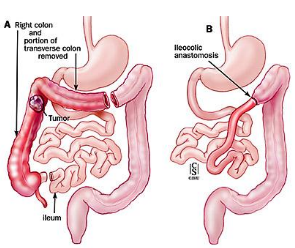
Manually extracted EMR data will be used for controls

Manually extracted CRC data (controls)
- high validity data
- CRC cancer admissions/5 yrs

CRC data 1997-2012 (cases)
- low validity
- approximately 10 000 admission

Statistical analyses
- Propensity scores
- Mutivariate modelling
- Scale space analyses

Sematic analyses/Natural Language Processing (NLP)



TROMSØ TELEMEDICINE LABORATORY

We will use our experiences to identify other adverse events

Example case: Colorectal cancer

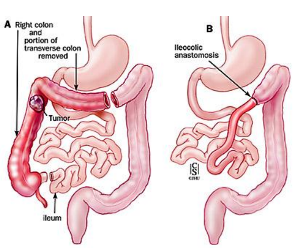
Anastomoses leakage, deep vein thrombosis, pulmonary embolism, wound infection, pneomonia, urinary tract infection, renal failure, myocardial infarction, and others

Expand to other diseases/conditions

Expand to other departments

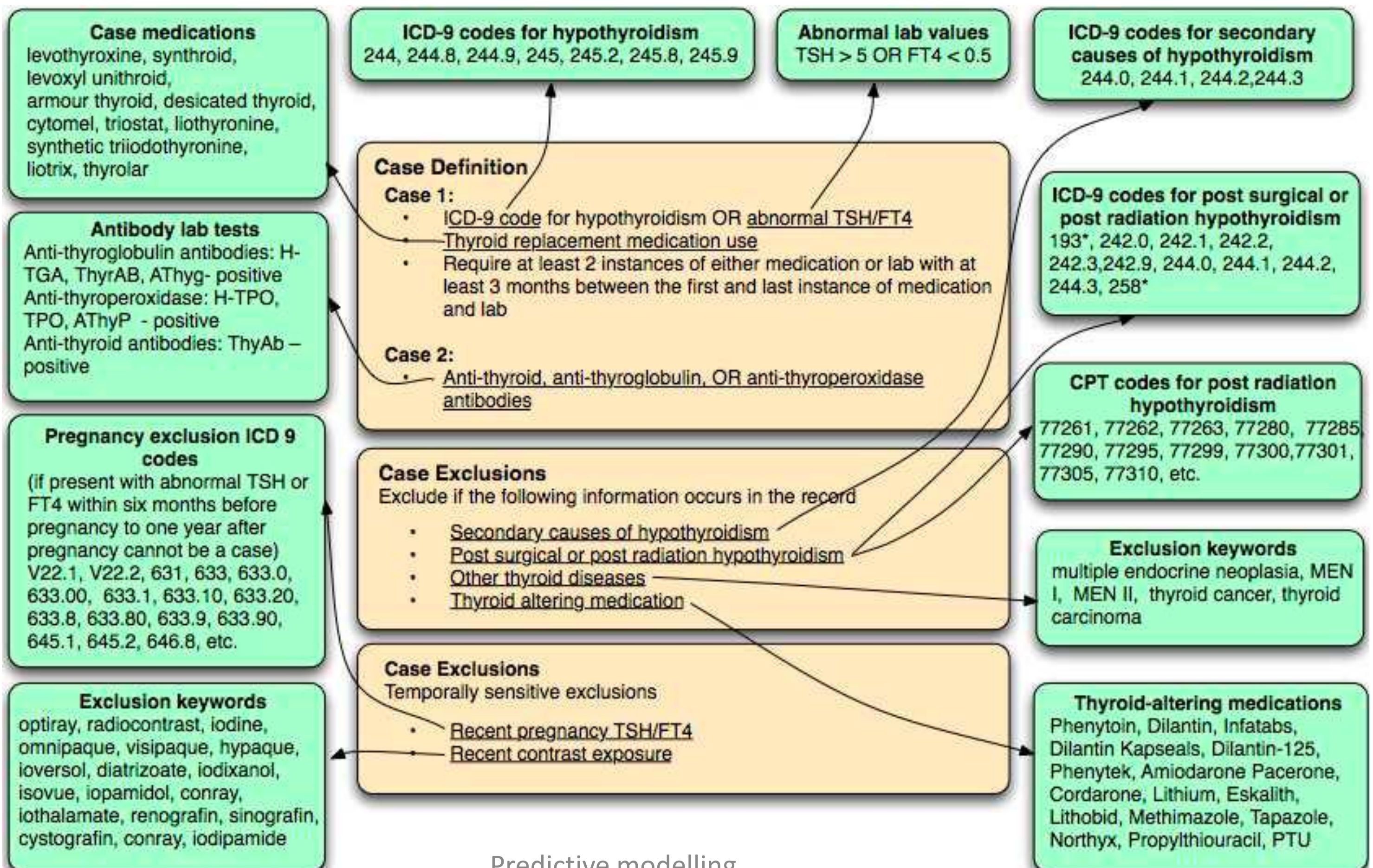
1) EMR application outcome assessment

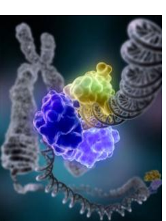
2) EMR applications for personalised medicine, process management and risk assessment



TROMSØ TELEMEDICINE LABORATORY

Disease phenotyping is algorithmic recognition of any cohort within EMR for a defined purpose



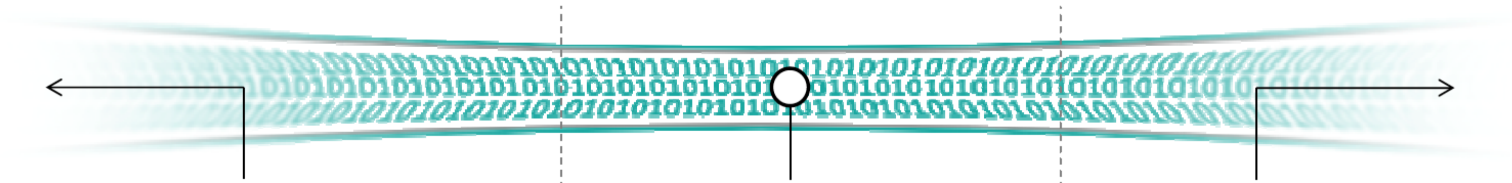


IBM Content and Predictive Analytics … *Ready for Watson*

Complements IBM Watson to analyze and visualize past, present and future scenarios in context

Question What is Known

Complement ICPA with **Watson for Healthcare** to get real time, confidence based answers with evidence based learning



Analyze and Visualize the Past

Understand trends, patterns, deviations, anomalies, context and more in large corpuses of historical clinical and operational information to reveal new insights

See the Present

Analyze and extract text from in-process documents or other information to find structured data errors … feed the results to other cases and systems

Predict the Future

Use predictive models and scoring to make more informed decisions through predictive and future scenario modeling

TEMA 23 SIDER OLJE OG GASS • SIDE 47-69

Teknisk Ukeblad

FOR DEG SOM SKAPER FREMTIDEN WWW. TU.NO

PROFILEN

–Vi er et folk av matte-angst

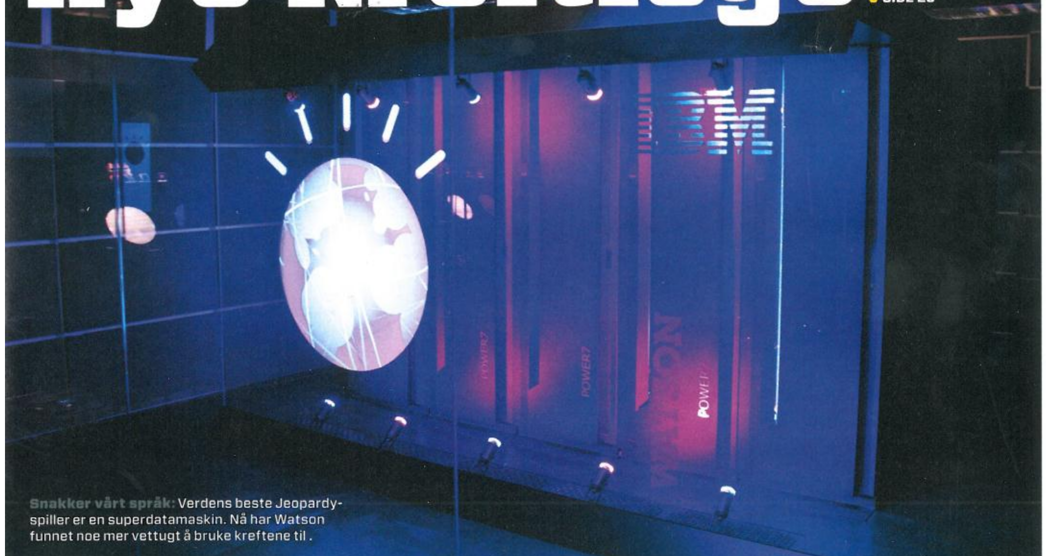
• SIDE 42

Kristin Halvorsen.

Ekspertene spår it-revolusjon:

Watson blir din nye kreftlege

• SIDE 26



Snakker vårt språk: Verdens beste Jeopardy-spiller er en superdatamaskin. Nå har Watson funnet noe mer vettugt å bruke kreftene til .

9 770040 235007

1712

159. ÅRGANG – NR. 17/10. MAI 2012
LØSSALG KR 69,-

340 000 LESERE UKENTLIG

AKTUELT

Mongstads skjebne er usikker

• SIDE 8

FORBRUKER

Galaxy SIII skal danke ut Iphone

• SIDE 38

Workshop TTL-IBM New York 30-31/5
Topic: predictive analytics and adverse outcomes

IBM WATSON

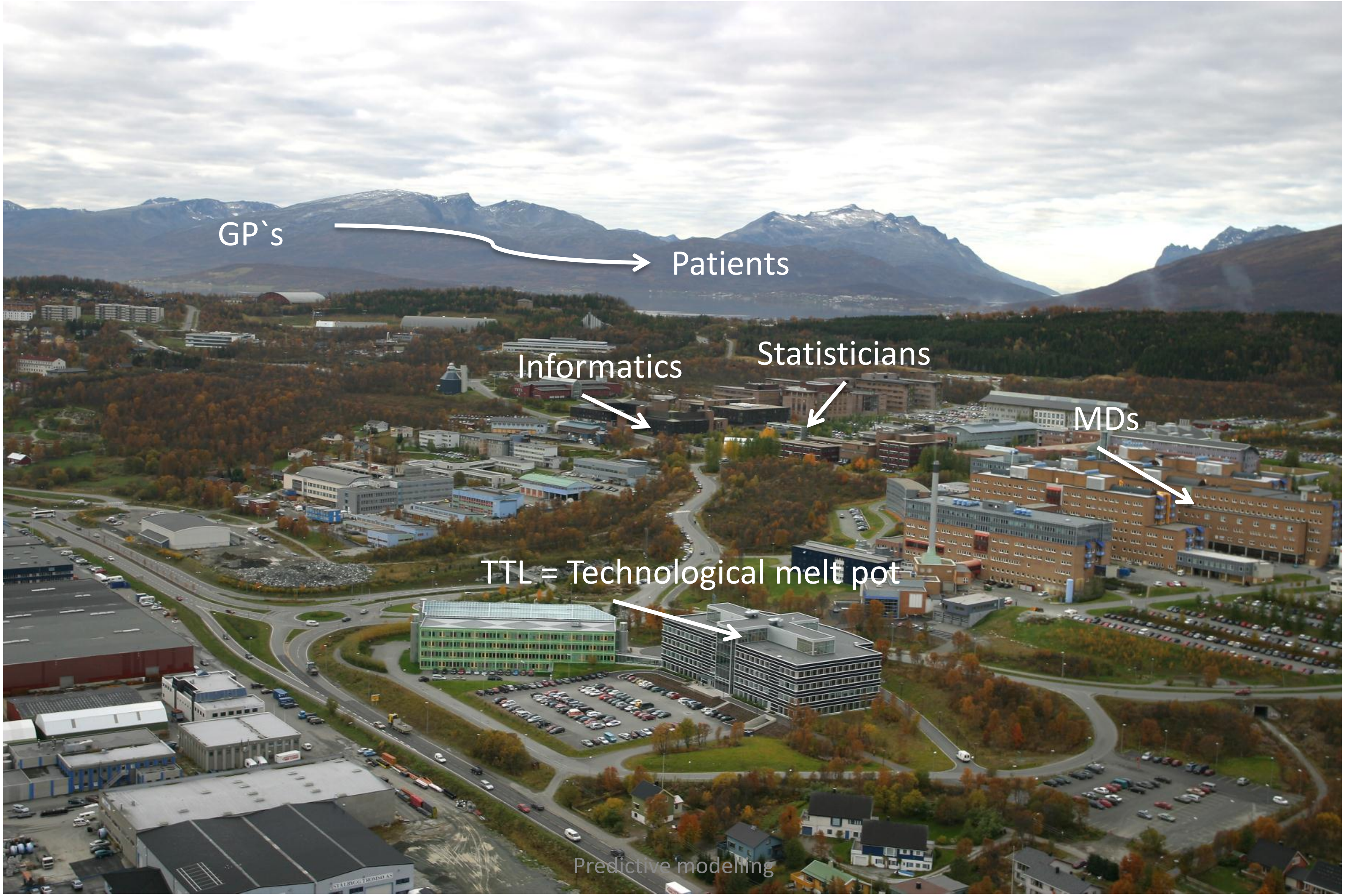
Clinical Decision Support: DeepQA
Martin S. Kohn, MD, MS, FACEP, FACPE
Chief Medical Scientist, Care Delivery Systems
IBM Research

© 2009

IBM Agenda for TTL - Day 1
Hawthorne Industry Solutions Lab

Time Demo Duration (minutes)
Topic
Speakers
Availability
09:00 AM 15 Welcome and Introductions
Comments: **Bob Stackhouse Proposed**
09:15 AM 90 TTL Overview and Briefing Objectives
Comments:The Medical Problem, Methods of Disease phenotyping, of unstructured EMR data , **TTL Proposed**
10:45 AM 15 Break
Comments:
11:00 AM 60 IBM Healthcare and Research Overview
Comments: **Joe Jasinski Proposed**
12:00 PM 30 General Discussion relative to TTL and IBM morning presentations
Comments:
12:30 PM 60 Lunch
Comments:
01:30 PM 60 Healthcare Analytics
Comments: **John Piccone Proposed**
02:30 PM 15 Break
Comments:
02:45 PM 60 Patient Similarity Analytics
Comments: **Shahram Ebadollahi Proposed**
03:45 PM 15 Review of Day 1 Topics and Action Items
Comments:
04:00 PM 0 Adjourn Day 1
Comments:

TROMSØ TELEMEDICINE LABORATORY



TROMSØ
TELEMEDICINE
LABORATORY

Get on Board the Medical Data Train—It Is Leaving the Station: Destination 2014.

Doarn, C. R., & Merrell, R. C. (2010). Telemedicine and e-Health, 16(7), 755–756.