Update in Clinical Informatics

(Warning: We are *not* a *serious* duo)

PCC Ojai, California
June 2021

Colin Banas, CMO, *Dr. First*
Bill Galanter, Assoc Prof, University of Illinois at Chicago

DrFirst

AMDIS Association of Medical Directors of Information Systems

University of Illinois
Hospital & Health Sciences System
Changing medicine. For good.

Review Methodology

Hmmm. What cool things did I read this year? What helps me fall asleep. Where can I find my jokes. I don't have enough to do as an industry slave.

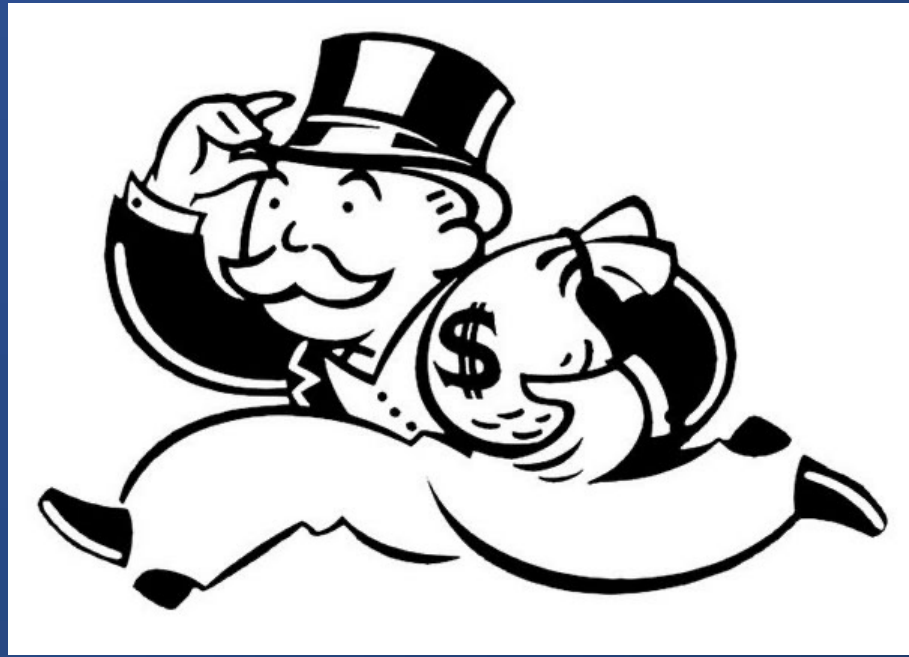
I am part time, losing my grants. I'm bored, bald, interested in unnecessarily complex methodology and statistics.

Prior Conflicts

20 years ago the poster child of Cerner reference visits when Cerner had only 1 hospital up and Epic was beginning to think about hospitals.

Now…

Conflicts



Dr. “Daddy Warbuck’s” Banas

zilch
nil
none
diddly squat
naught

Topics Covered

Colin

- Open Notes
- AI
- Frameworks and Regulatory Stuff coming your way soon
- COVID (sorry, couldn't help it) and new stuff

Bill

- Methodology
- Clinical Decision Support
- AI
- Inpatient Order Voiding
- Robots (oh my!)

Bill's Review Methodology

"Adverse Drug Reaction Reporting Systems"[MESH] OR "Biological Ontologies +"[MESH] OR "Clinical Decision Rules"[MESH] OR "Clinical Laboratory Information Systems"[MESH] OR "Clinical Pharmacy Information Systems"[MESH] OR "Community Networks"[MESH] OR "Consumer Health Informatics"[MESH] OR "Decision Making, Computer-Assisted"[MESH] OR "Decision Support Systems, Clinical"[MESH] OR "Decision Support Techniques"[MESH] OR "Diagnosis, Computer-Assisted +"[MESH] OR "Electronic Prescribing"[MESH] OR "Health Information Exchange [L01.313.500.500]"[MESH] OR "Health Information Systems"[MESH] OR "Health Smart Cards"[MESH] OR "Hospital Information Systems"[MESH] OR "Information Systems"[MESH] OR "Integrated Advanced Information Management Systems"[MESH] OR "Knowledge Bases"[MESH] OR "Medical Informatics Applications"[MESH] OR "Medical Informatics Computing"[MESH] OR "Medical Order Entry Systems"[MESH] OR "Medical Records Systems, Computerized"[MESH] OR "Nursing Informatics"[MESH] OR "Prescription Drug Monitoring Programs"[MESH] OR "Public Health Informatics"[MESH] OR "Radiology Information Systems"[MESH] OR "Reminder Systems"[MESH] OR "Teleradiology"[MESH] OR "Therapy, Computer-Assisted +"[MESH] ORclinical informatics OR Appl Clin Inform OR appl med inform OR bmc med inform decis mak OR comput inform nurs OR int j med inform OR j amia OR j clin bioinforma OR j innov health inform OR j med internet res OR j med syst OR med inform

NOT

"COVID-19"[Mesh] OR "SARS-CoV-2"[Mesh] (***Editorial Decision***)

AND

Abstract Corpus ← (51,938) **1/1/20-4/30/21 AND English AND Abstract**

AND

"Clinical Trial" OR "Observational Study" OR "Meta-Analysis" OR (4,160)
"Comparative Study" (Study)

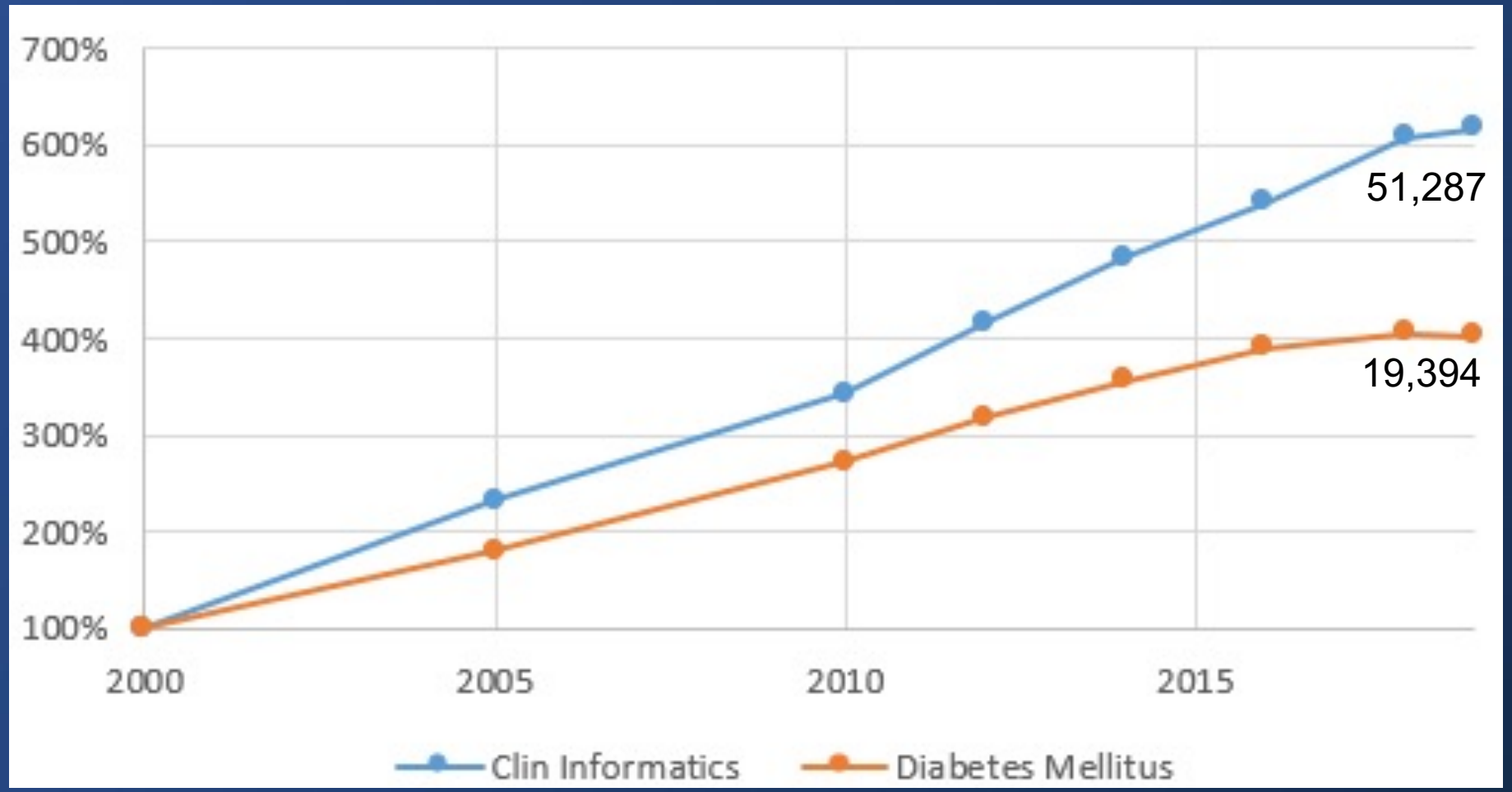
AND

Select papers to present ← (1067) **"Clinical Trial"**

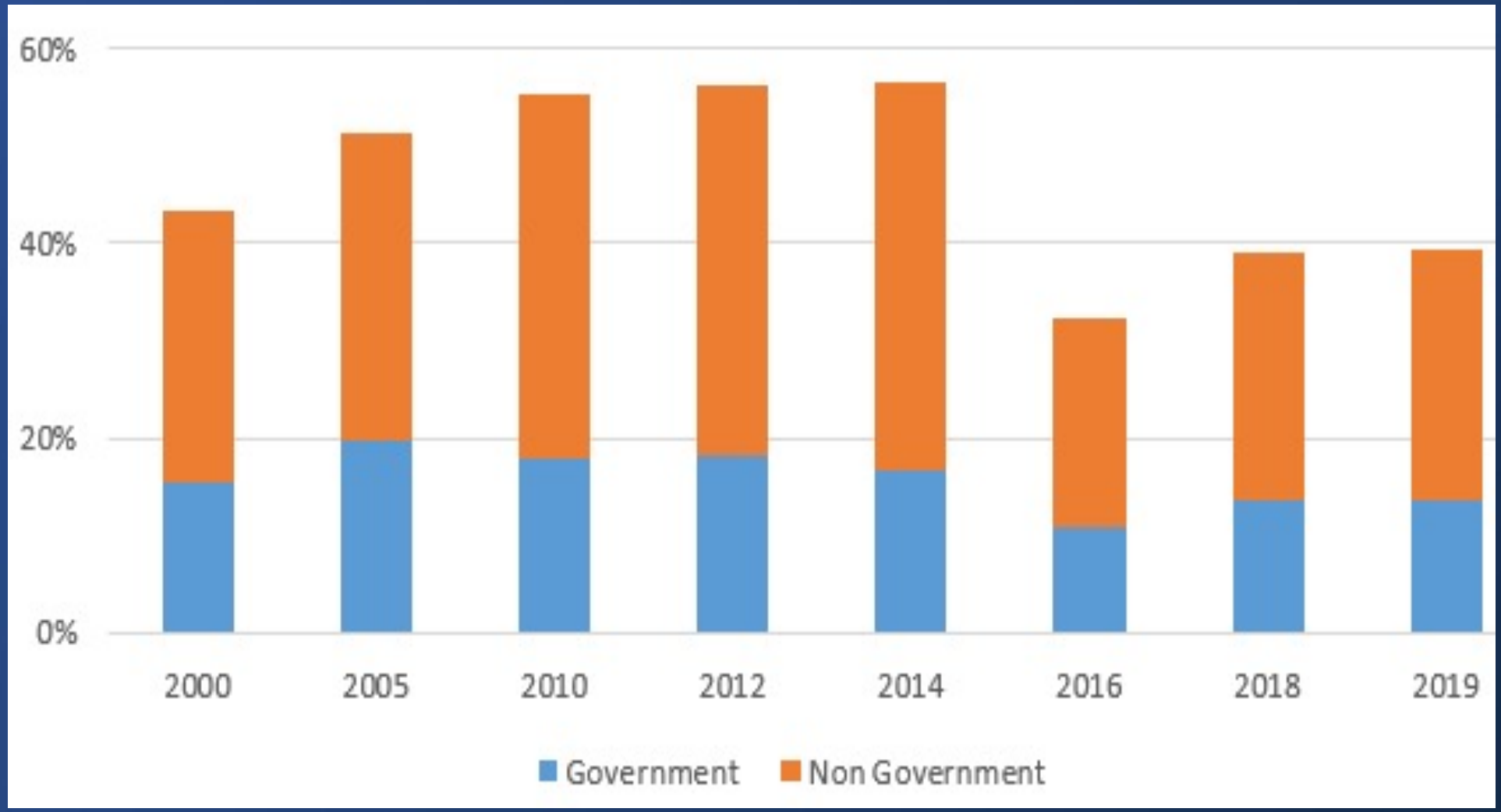
AND

"Randomized Controlled Trial" (793)

Growth in Publications



% of publications with funding clinical informatics



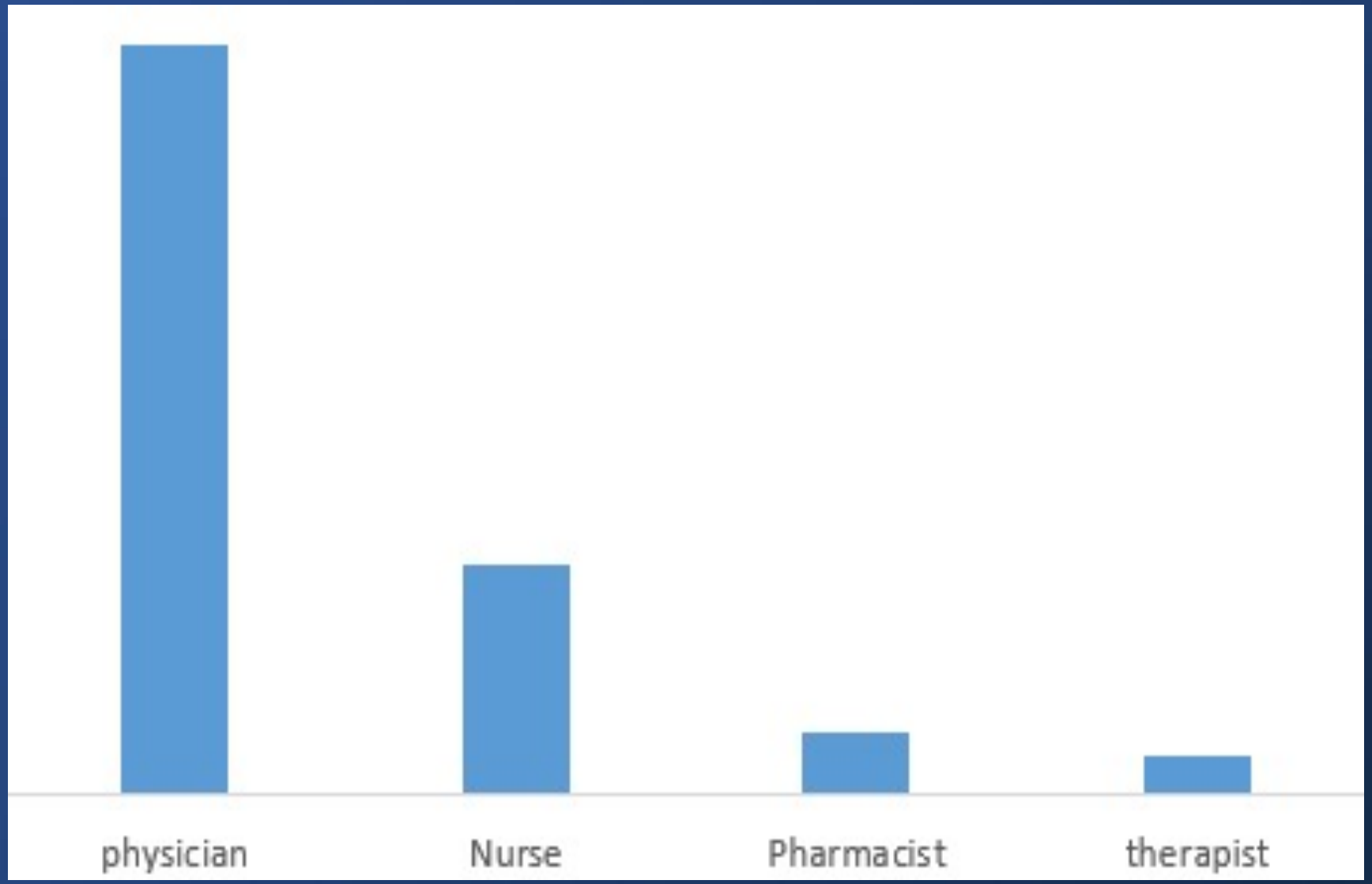
BS/Study Ratio®

BS: Opinions, thoughts, anecdotes, cases, whatever, etc. / ***Study:*** experiments, retro analysis, observations, some type of study.

	Studies	Papers	BS/E Ratio
Chest Pain (2019)	69	773	10.2
Diabetes (2019)	1,549	19,394	11.5
Clinical Informatics (2019)	1,599	51,287	31.1
COVID-19 (All)	621	47,849	76.1
Deep Learning (2019)	17	2068	120.6
Blockchain (2019)	0	123	∞

® W. Galanter & C. Banas 2012,14,15,16,18,21

Which clinician's have mentions in the "Corpus" (N= 51,938)



What's in the Abstract Corpus?

General Themes (remove clinical and technology)

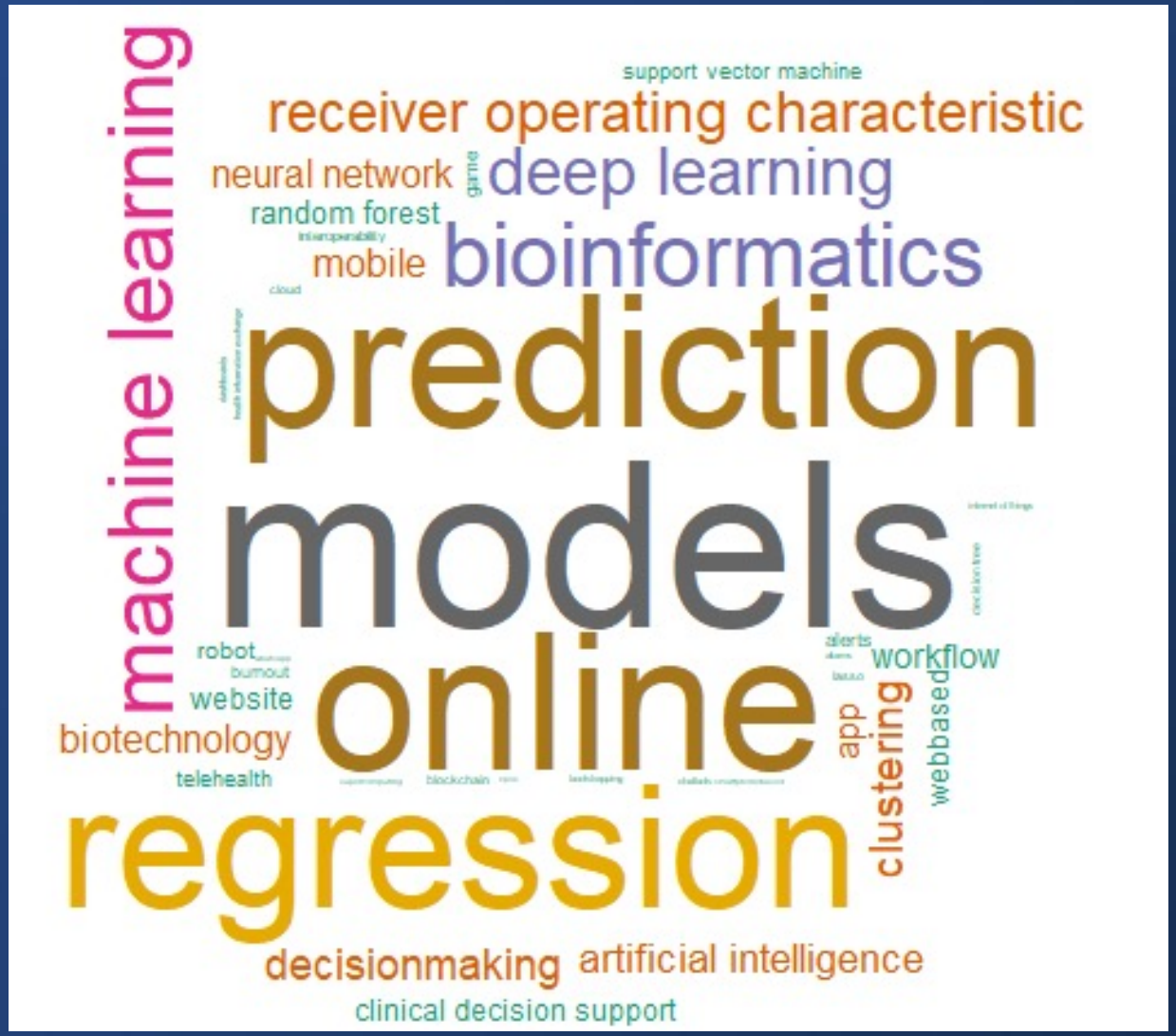
*Done in R by someone >55

What's in the Abstract Corpus?

Clinical Themes (remove general and technology)

What's in the Abstract Corpus?

Informatics Themes (remove general and clinical)



Some repeated themes in the Trial Corpus

Automated reminders: portals, texts, phone calls, letters, e-mail

Web-based, Mobile App: gamification, "serious games", virtual reality, chatbot, WeChat, WhatsApp, robotic seal, social robots, *Lost in Space* robots

-Affective Disorders
-Alcoholism
-Autism
-CHF
-Dementia
-Diabetes
-Gait Training
-Hospitalized Children
-HTN
-Insomnia
-MS
-Opioid use
-Occupational Stress
-PT
-Nutrition
-Rehab
-Schizophrenia
-smoking cessation
-stroke

CDS

-Imaging; appendicitis,
-Mental Health
-epilepsy
-Cancer prevention
-DM I insulin dosing with AI
-Rx of UTI's
-polyneuropathy
-DM II
-AKI

AI, deep learning, machine learning, machines learning to dig deeper etc.

-EKG→LV dysfunction
-EEG→seizures
-imaging of drusen
-out-of-hospital cardiac arrest
-Colonoscopy Adenoma's
-CT for cancer
-Retinal Analysis
-Malignant pathology
-transcranial DC stimulation
-Prognosis s/p spine surgery
-Radiation therapy planning
-Emergency dispatching

Transition Comedy Slide

Open Notes Updates by Colin

Open Notes – Patient Access

OurNotes has two principal goals:

- To engage patients (and often their families) more actively in their care, and
- To help make visits more focused and efficient for both patients and clinicians

The hypotheses: *OurNotes* will:

- increase patient engagement
- bring more focus and structure to encounters
- promote shared decision-making, and
- off-load some work from clinicians

https://ctlin.blog/2020/11/11/uchealth-launches-ournotes-how-patients-co-author-clinic-progress-notes/

Welcome! Thank you for helping us prepare for your visit. Your input is very

1. **How have you been since your last visit?** For example, have you had any:
   - New symptoms, health worries, or life changes?
   - Visits to a hospital, emergency room, tests, or visits to specialty doctor offices?
   - Medication changes?

   These great tips can help you explain your medical problems so your doctor or nurse can best help you.

   2,000 character limit (about 300 words)

1. **What are the most important things you would like to discuss at your visit?** (List up to 3)

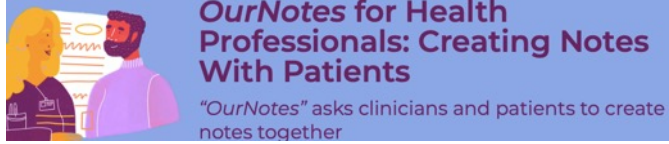
   300 character limit total (about 50 words)

   1.
   2.
   3.

3. **If possible, please review your medication list. Is it correct?** If yes, go to the next question. If not, what is wrong or missing?

https://www.opennotes.org/ournotes-professionals/

Our Notes – Preliminary Findings



- All UC Clinics live as of November 2020
- 90% of providers (physicians and APP's: advance practice providers) responding to surveys viewed OurNotes positively and wanted to continue, as did over 90% of patients who participated
- About 15-20% of patients who have an appointment respond send an OurNote, and providers are using the notes regularly
- "How to write an open note"

JGIM
Journal of General Internal Medicine

Do Words Matter? Stigmatizing Language and the Transmission of Bias in the Medical Record

Anna P. Goddu, MSc[1], Katie J. O'Conor, BA[1], Sophie Lanzkron, MD, MHS[2], Mustapha O. Saheed, MD[3], Somnath Saha, MD, MPH[4,5], Monica E. Peek, MD, MPH, MSc[6], Carlton Haywood, Jr., PhD, MA[2], and Mary Catherine Beach, MD, MPH[1]

[1]Johns Hopkins University School of Medicine, Baltimore, MD, USA; [2]Division of Hematology, Johns Hopkins University School of Medicine, Baltimore, MD, USA; [3]Department of Emergency Medicine, Johns Hopkins University School of Medicine, Baltimore, MD, USA; [4]Section of General Internal Medicine, VA Portland Health Care System, Portland, OR, USA; [5]Division of General Internal Medicine and Geriatrics, Oregon Health and Science University, Portland, OR, USA; [6]Section of General Internal Medicine, The University of Chicago, Chicago, IL, USA.

https://ctlin.blog/2020/11/11/uchealth-launches-ournotes-how-patients-co-author-clinic-progress-notes/

Sharing Clinical Notes in Psychotherapy: A New Tool to Strengthen Patient Autonomy

Charlotte R. Blease[1], Jan Walker[1], John Torous[2] and Stephen O'Neill[1]*

[1] OpenNotes, General Medicine and Primary Care Research, Beth Israel Deaconess Medical Center and Harvard Medical School, Boston, MA, United States, [2] Department of Psychiatry, Beth Israel Deaconess Medical Center and Harvard Medical School, Boston, MA, United States

Sharing notes with mental health patients: balancing risks with respect

Charlotte R Blease • Stephen O'Neill • Jan Walker • Maria Hägglund • John Torous

Published: February 11, 2020 • DOI: https://doi.org/10.1016/S2215-0366(20)30032-8 • Check for updates

- Harvard / Open Notes – Thought piece regarding exposure of Psych therapy notes
- These note types are indeed currently exempt from 21st CURES but should they be?
- "We propose that giving patients access to their clinical notes may provide an important route to support informed consent in psychotherapy by enhancing patient autonomy, procedural knowledge, and recall about psychotherapy processes. "

Sharing Psychotherapy Notes with Patients: Therapists' Attitudes and Experiences

Hannah Chimowitz, Stephen O'Neill, Suzanne Leveille, Katrina Welch, Jan Walker

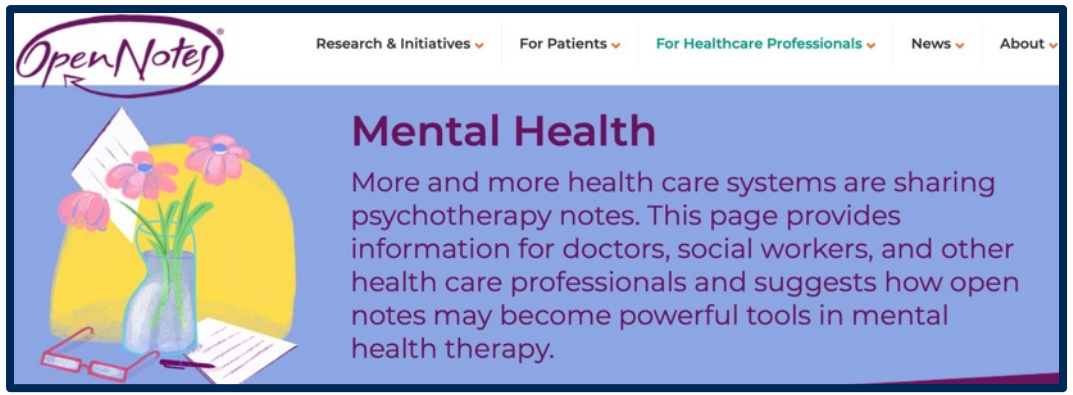
Social Work, Volume 65, Issue 2, April 2020, Pages 159–168,
https://doi.org/10.1093/sw/swaa010
Published: 01 April 2020 **Article history** ▾

https://www.opennotes.org/mental-health-professionals/

Psychotherapists may exclude notes of any type that may cause harm to the patient or others should the patient have access. **However, the rule specifically states that psychological distress does not meet the definition of harm (Torous, 2020).**

- Any notes designated as "psychotherapy notes" are excluded from the Open Notes Rule as long as they are stored separately. However, if the psychotherapy notes reference content that is considered *medical record notes*, they cannot be blocked. Medical record notes include:
  - Diagnosis
  - Symptoms
  - Functional status
  - Treatment plans
  - Prognosis
  - Progress to date
  - Session start and stop times
  - Test results
  - The modalities and frequencies of treatment furnished
  - Medication prescription and monitoring

OpenTherapy Notes



Demonstrating respect and reducing stigma

Empowering patients

- *Plan of care recall and adherence*

Organizing care and tracking progress

Providing a tool for behavior change

Enhancing trust and the therapeutic relationship
- *Demystify the doctor speak*

Making care safer

- *Patient "oversight" on the plan of care, second set of eyes*

Potential for reducing workload

- *Patient doesn't need to call the doctor back to recall*

Open Notes in Oncology: Patient versus Oncology Clinician Views

Liz Salmi • Zhiyong J. Dong • Bertram Yuh • Jan Walker • Catherine M. DesRoches

Published: October 08, 2020 • DOI: https://doi.org/10.1016/j.ccell.2020.09.016 • Check for updates

Cancer Cell

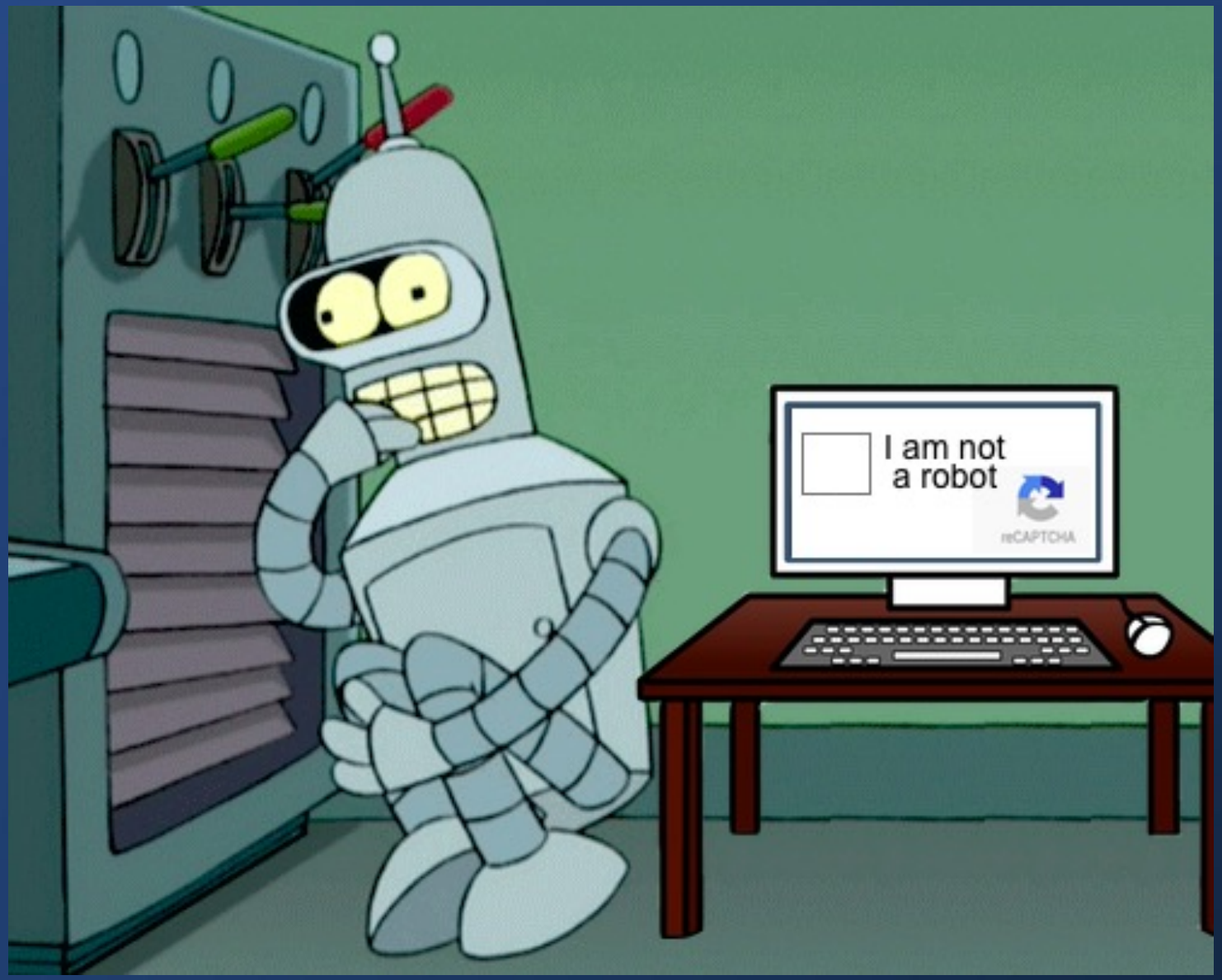
- Analyzed data from surveys from 3 health systems regarding perceptions of OpenNotes
- Isolated the data identifiable from oncology patients and oncology providers
- Clinician Views and Patient Views had a large difference
- Special shout out to Paul Fu, CT Lin, Everett Weiss

	Providers	Patients
Open Notes a good idea?	70%	98%
Can help patients be prepared for a visit?	28%	56%
Patients will be (or were) confused by notes?	44%	4%
Were contacted (or did contact) about contents of the notes?	Infrequently (89%)	23% of time

https://doi.org/10.1016/j.ccell.2020.09.016

Transition Comedy Slide

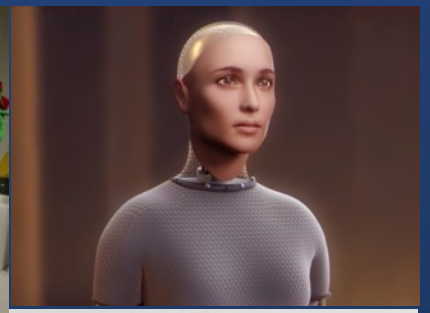
Robots by
Bill

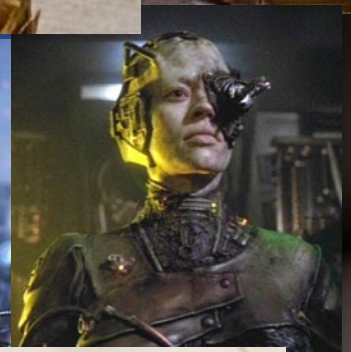
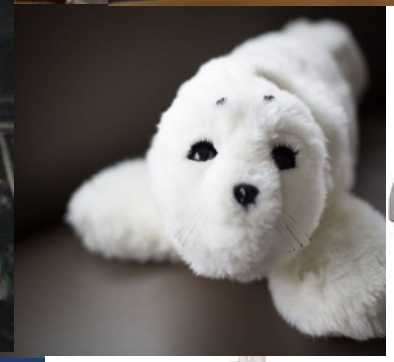


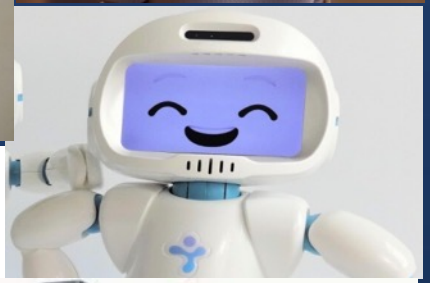
Which are real *clinical* Robots?











The “real” Robots

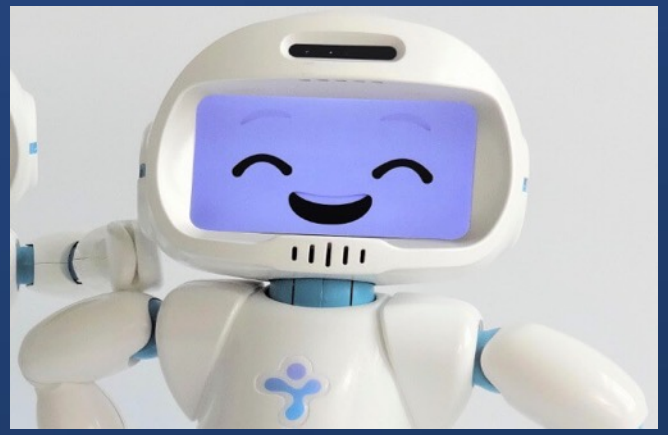
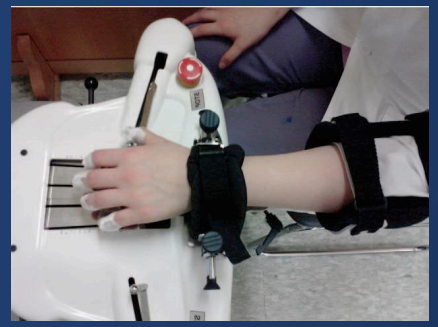
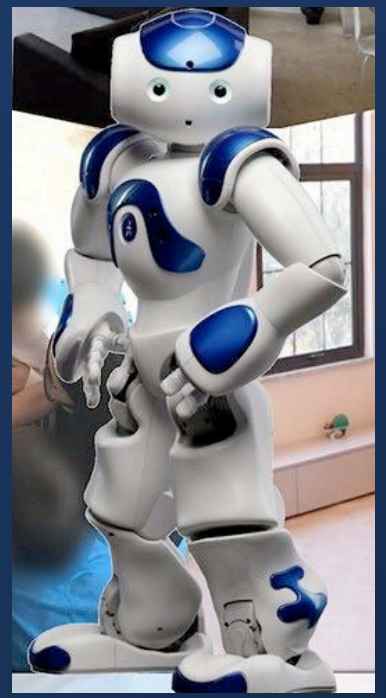
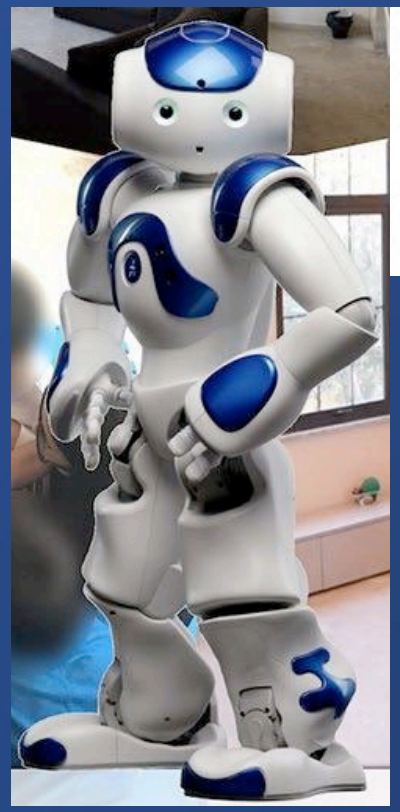


Fig. 2. *Gait Exercise Assist Robot (GEAR)*





A Social Robot for Autism Spectrum patients



Outcomes of a Robot-Assisted Social-Emotional Understanding Intervention for Young Children with Autism Spectrum Disorders

Flavia Marino[1] · Paola Chilà[1] · Stefania Trusso Sfrazzetto[1] · Cristina Carrozza[1] · Ilaria Crimi[1] · Chiara Failla[1] · Mario Busà[1] · Giuseppe Bernava[1] · Gennaro Tartarisco[1] · David Vagni[1] · Liliana Ruta[1] · Giovanni Pioggia[1]

Marino F, Chilà P, Sfrazzetto ST, Carrozza C, Crimi I, Failla C, Busà M, Bernava G, Tartarisco G, Vagni D, Ruta L, Pioggia G. Outcomes of a Robot-Assisted Social-Emotional Understanding Intervention for Young Children with Autism Spectrum Disorders. J Autism Dev Disord. 2020 Jun;50(6):1973-1987. PMID: 30852783.

A Social Robot for Autism Spectrum patients

-Group-based CBT

-N=14, RCT

-Designed to be implemented with the assistance of a social robot.

-Robot actively interacting with the children and providing verbal antecedents, prompts and reinforcing consequences.

-1 Clinical Site, Italy

Marino F, Chilà P, Sfrazzetto ST, Carrozza C, Crimi I, Failla C, Busà M, Bernava G, Tartarisco G, Vagni D, Ruta L, Pioggia G. Outcomes of a Robot-Assisted Social-Emotional Understanding Intervention for Young Children with Autism Spectrum Disorders. J Autism Dev Disord. 2020 Jun;50(6):1973-1987. PMID: 30852783.

A Social Robot for Autism Spectrum patients

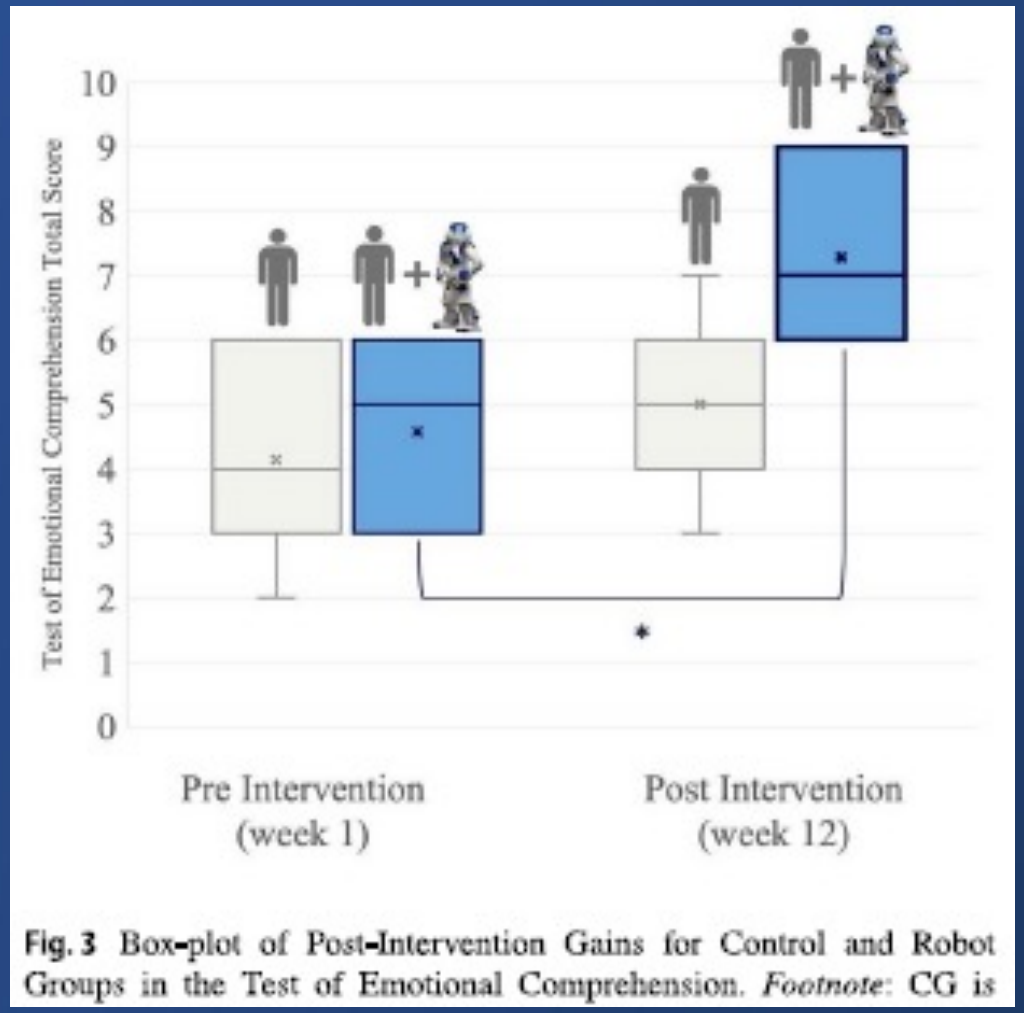
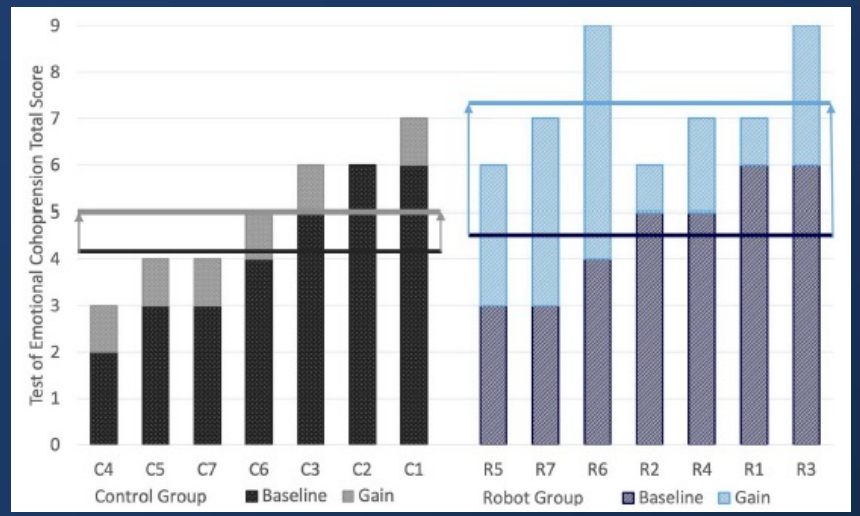


Fig. 3 Box-plot of Post-Intervention Gains for Control and Robot Groups in the Test of Emotional Comprehension. *Footnote*: CG is

Test of Emotional Comprehension



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Transition Comedy Slide

Frameworks and Regulatory Topics by Colin

Article | Open Access | Published: 19 November 2020

Push Button Population Health: The SMART/HL7 FHIR Bulk Data Access Application Programming Interface

Kenneth D. Mandl ✉, Daniel Gottlieb, Joshua C. Mandel, Vladimir Ignatov, Raheel Sayeed, Grahame Grieve, James Jones, Alyssa Ellis & Adam Culbertson

npj | digital medicine

- In March 2020 CDC only had clinical data on underlying health conditions for 5.8% of COVID-19 cases. There is a dire need for real-time clinical data to power robust bio-surveillance.
- The second API, SMART/HL7 FHIR Bulk Data Access will enable access to patient-level data across a patient population
- The result is a now-regulated capacity, required in certified health information technology by 2022, to export FHIR data, from any EHR, in an easily consumable NDJSON formatted flat file

https://www.nature.com/articles/s41746-020-00358-4

Bulk FHIR

By 2022, certified health information technology will require a bulk FHIR server whereby the organization that owns the IT (e.g., EHR or cloud-hosted FHIR server) can allow authorized software clients to interrogate the server and return population datasets

The data that will be made available via the API are defined by the U.S. Core Dataset for Interoperability (USCDI), which will be augmented over time

- *Data at the Point of Care* (https://dpc.cms.gov/)
    - Giving physicians access to patient claims data. Fee for service providers supply rosters of active patients and CMS returns FHIR-formatted bulk data files.
- The *Beneficiary Claims Data API* (https://bcda.cms.gov/)
    - Provides accountable care organizations that participate in a Shared Savings Program access to specific Medicare claims data, in bulk FHIR format, for their assignable/prospectively assigned beneficiaries

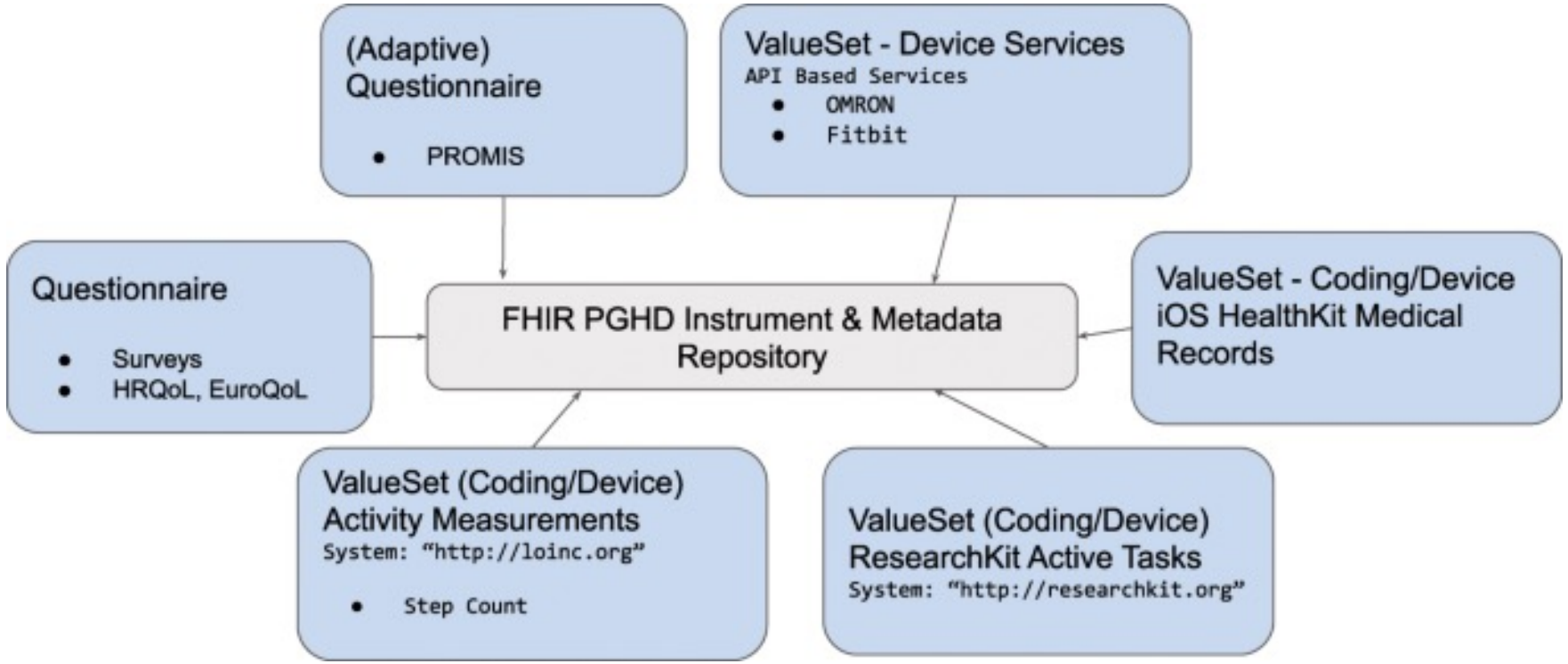
Article | Open Access | Published: 23 January 2020

SMART Markers: collecting patient-generated health data as a standardized property of health information technology

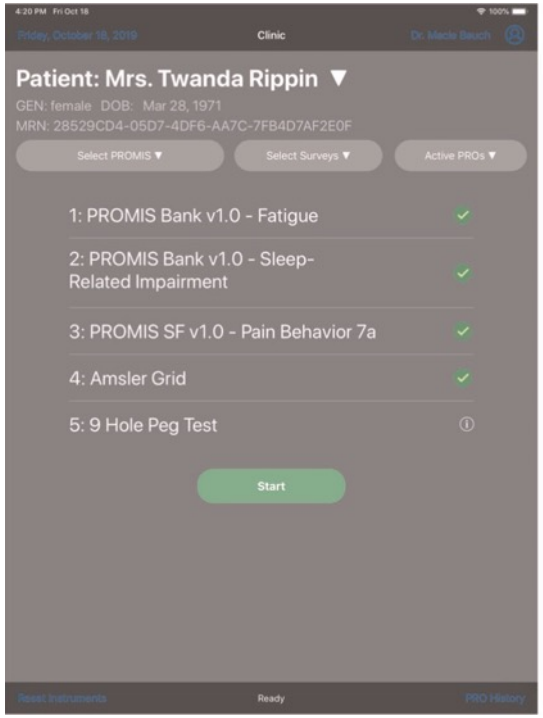
Raheel Sayeed, Daniel Gottlieb & Kenneth D. Mandl

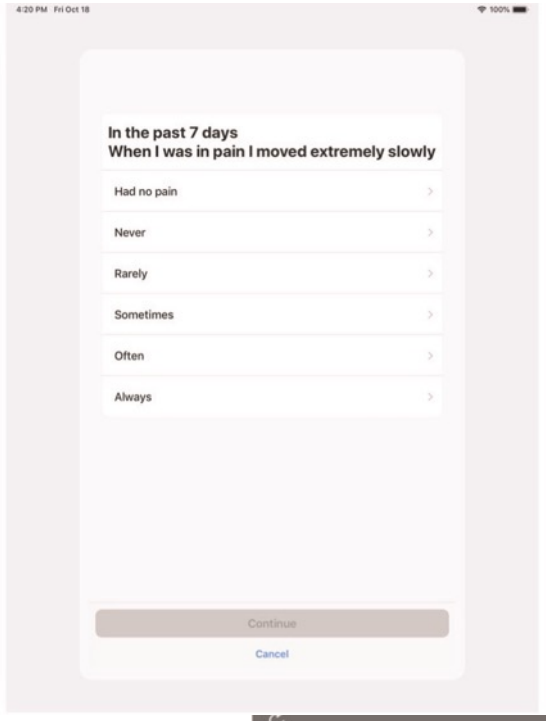
npj | digital medicine

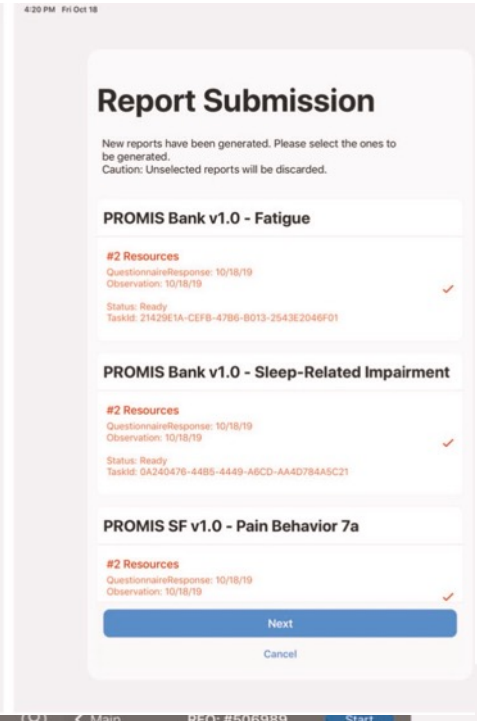
- Based on SMART on FHIR – represents a framework encapsulating functionality needed for rapid deployment of patient and provider generated health data apps at scale

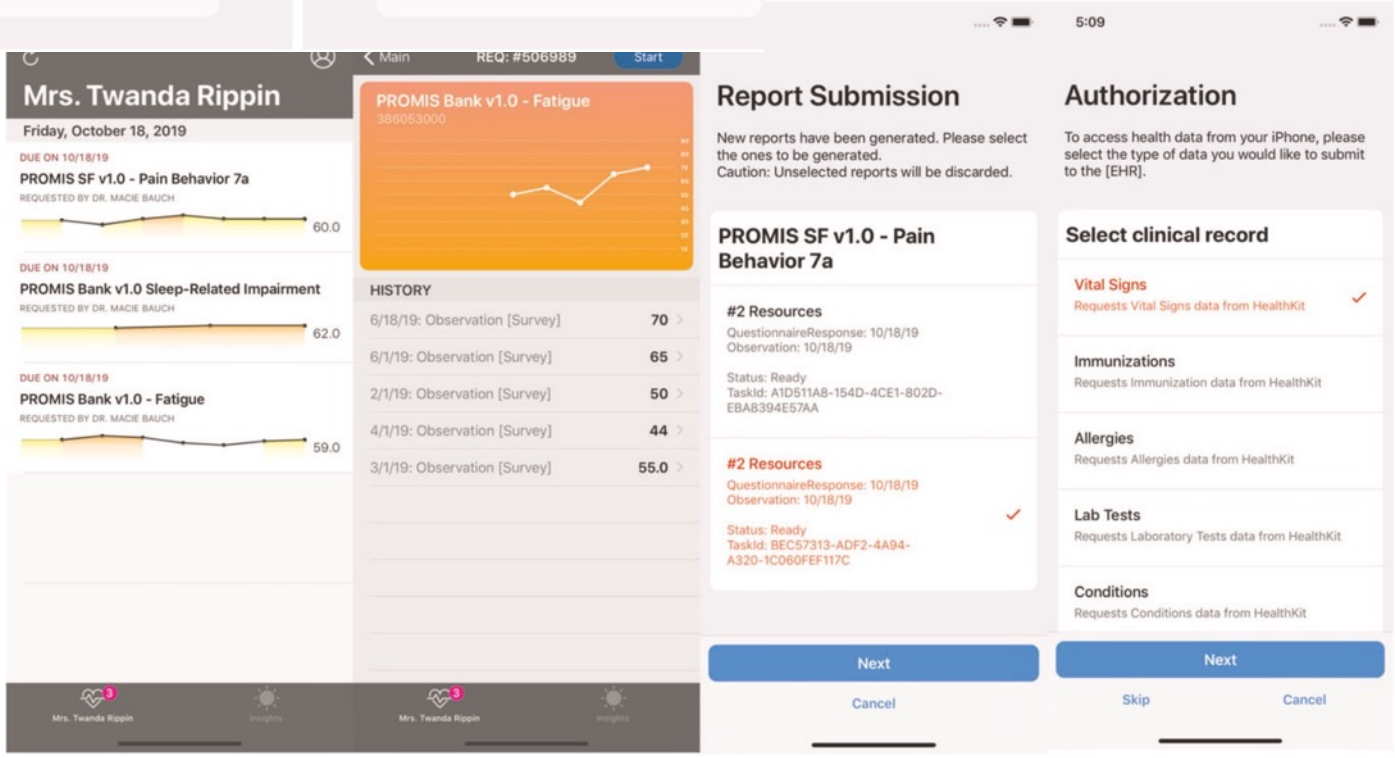


https://www.nature.com/articles/s41746-020-0218-6









https://www.nature.com/articles/s41746-020-0218-6

The impact of electronic health record–integrated patient-generated health data on clinician burnout

Jiancheng Ye*

Feinberg School of Medicine, Northwestern University, Chicago, Illinois, USA

*Corresponding Author: Jiancheng Ye, Feinberg School of Medicine, Northwestern University, 633 N. Saint Clair St, Chicago, IL 60611, USA; jiancheng.ye@u.northwestern.edu

Received 30 June 2020; Editorial Decision 11 January 2021; Accepted 26 January 2021

PGHD Domain	Definition	Association With Burnout
PROs	• PROs are assessments of patients' health conditions reported directly from patients in the form of questionnaires.[7] • Health-related outcomes reported by patients have higher accuracy than clinical reports.[8] • Patient reporting can improve patient–provider communication, patient satisfaction, and symptom management.[9,10] • Widespread adoptions of PROs in performance evaluation cater to the growing interests in integrating PROs into EHR systems and patient portals.[11]	Main barriers to integrating PROs data into EHR: 1. Work overload. Clinicians are concerned that adding PROs will make their work burdensome[12]; 2. Lack of actionable guidance[13]; 3. Lack of validity of PRO scores to sufficiently support clinical decision-making; 4. Lack of financial incentives. Clinicians have no motivation to increase their job responsibilities without improved payment models[14]; 5. Low level of engagement of patients in completing PRO assessment. Providers have to spend extra time to explaining the purpose and assisting patients in completing the tasks.[13]
mHealth	• Mobile apps and wearable or portable devices that could be connected with smartphones have been increasingly harnessed to support health monitoring and management.[15] • Healthcare systems have been interdependent on EHR capacities due to the widespread adoption and legislation of meaningful use.[16] • Integration of data generated by various devices into EHR becomes a novel and critical capacity of hospital information systems.	Main barriers to integrating mHealth data into EHR: 1. Wearable device data are too noisy to be useful before compilation and interpretation by HCPs[17]; 2. HCPs may experience more alert fatigues in the clinical support systems[18]; 3. While some health systems and vendors have begun to develop user-centered design approaches to adapt workflows and collaborate with third-party wearable devices to improve the integration of PGHD and EHR, data interoperability and visualization still impede the connection between wearable PGHD and EHRs.[19]

doi: 10.1093/jamia/ocab017

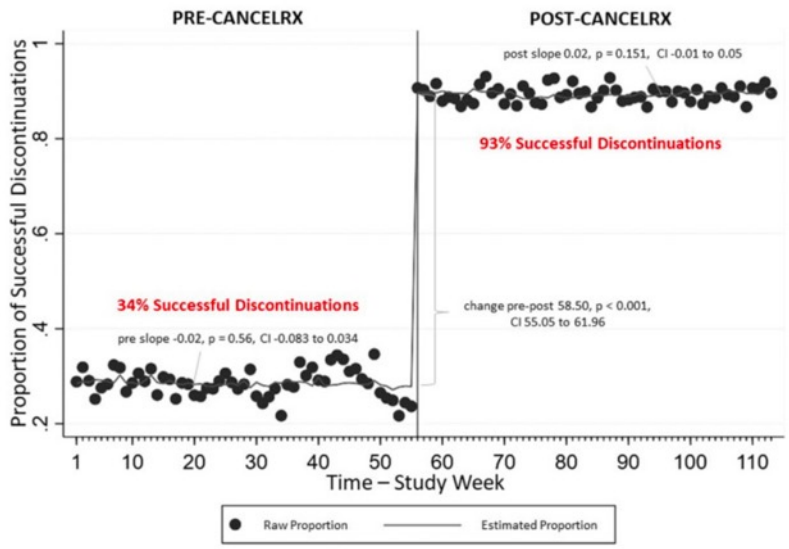
CancelRx: a health IT tool to reduce medication discrepancies in the outpatient setting

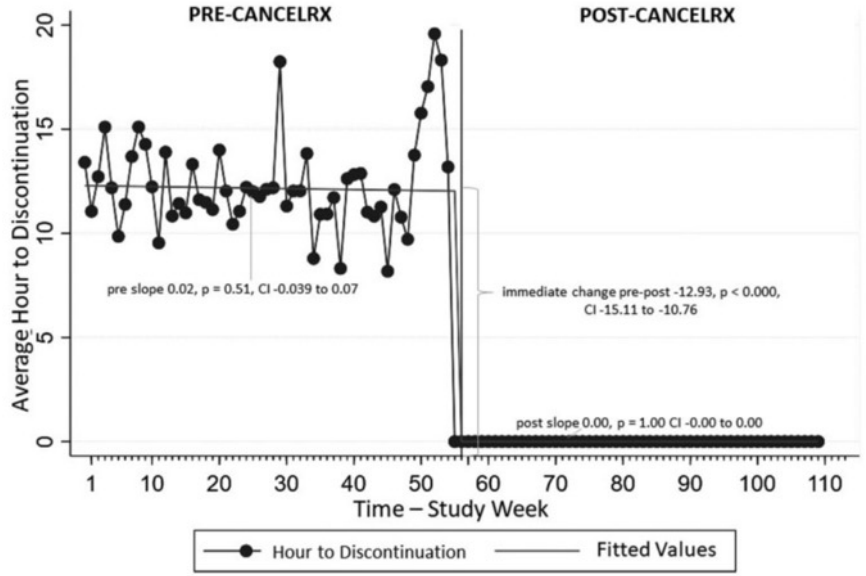
Taylor L. Watterson,[1] Jamie A Stone,[1] Roger Brown,[2,3] Ka Z Xiong,[4] Anthony Schiefelbein,[2] Edmond Ramly,[3,5] Peter Kleinschmidt,[3] Michael Semanik,[3,*] Lauren Craddock,[6] Samantha Pitts,[7] Taylor Woodroof,[7] and Michelle A. Chui[1]

- CancelRx Transaction NCPDP standard is over 10 years old but poorly adopted
- Mismatched medication lists (EHR vs Pharmacy) is no bueno
- 5% of medications stopped in EHR end up being dispensed / 34% of those are high risk
- University of Wisconsin
- 12 months of PRE and POST data (PRE = phone calls / faxes / messages attached to eRx to cancel)
- 350k cancelled Rx across 15 pharmacies (within the same health system) in those 2 years

CancelRx

	PRE (OLD SCHOOL CANCEL)	POST IMPLEMENTATION
Successful Cancellation across both systems	34%	93%
Clinic = PCP	26%	93%
Clinic = Specialty	44%	93%
Time to Medication Discharge	13 hours	Instant





CancelRx

Limitations

- "Closed Loop System"
- Commercial pharmacy without enabling it led to failed messages in the inbox = clutter
- Inbox clutter = burnout

JOHNS HOPKINS
UNIVERSITY

http://ncpdpfoundation.org/pdf/JHCancelRxReport.pdf

Impact of CancelRx on Discontinuation of Controlled Substance Prescriptions

Taylor L. Watterson, Jamie A Stone, Aaron Gilson, Roger Brown, Ka Z Xiong, Anthony Schiefelbein, Edmond Ramly, Peter Kleinschmidt, Michael Semanik, Lauren Craddock, Samantha Pitts, Taylor Woodroof, Michelle Chui

doi: https://doi.org/10.1101/2021.01.12.21249700

Transition Comedy Slide

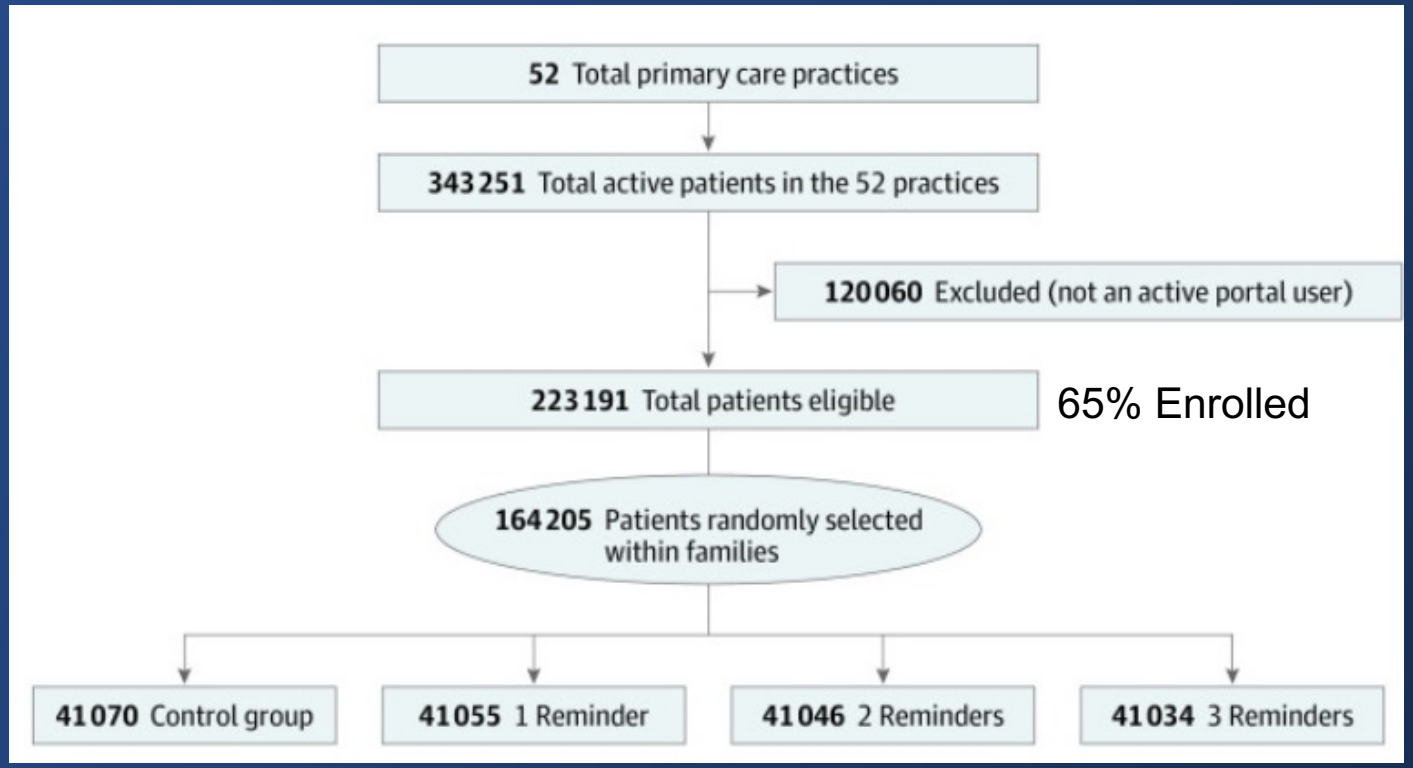
Clinical Decision Support Articles from Bill

Automated reminders for Influenza

Effect of Patient Portal Reminders Sent by a Health Care System on Influenza Vaccination Rates

A Randomized Clinical Trial

Peter G. Szilagyi, MD, MPH; Christina Albertin, BSN, MPH; [...]; and Carlos Lerner, MD, MPhil



Szilagyi PG, Albertin C, Casillas A, Valderrama R, Duru OK, Ong MK, Vangala S, Tseng CH, Rand CM, Humiston SG, Evans S, Sloyan M, Lerner C. Effect of Patient Portal Reminders Sent by a Health Care System on Influenza Vaccination Rates: A Randomized Clinical Trial. JAMA Intern Med. 2020 Jul 1;180(7):962-970. PMID: 32421168

Automated reminders for Influenza

Table 1. Demographic Characteristics of the Study Sample[a]

Characteristics	Patients, %				
		Control	Intervention		
	Total (N = 164 205)	0 Reminders (n = 41 070)	1 Reminder (n = 41 055)	2 Reminders (n = 41 046)	3 Reminders (n = 41 034)
Age group, y					
0.5-17	7.4	7.3	7.4	7.4	7.3
18-64	74.0	73.8	73.9	74.1	74.0
≥65	18.7	18.8	18.6	18.5	18.7
Female	58.3	58.4	58.3	58.2	58.4
Insurance					
Private	85.2	85.1	85.3	85.2	85.1
Public	13.5	13.5	13.4	13.6	13.6
Other or unknown	1.3	1.4	1.3	1.3	1.3
Race					
White	57.3	57.3	57.5	57.2	57.1
Black	4.6	4.4	4.6	4.7	4.8
Asian	10.3	10.1	10.4	10.3	10.3
Other or unknown	27.8	28.2	27.6	27.7	27.9
Hispanic ethnicity	9.6	9.5	9.6	9.8	9.6

Szilagyi PG, Albertin C, Casillas A, Valderrama R, Duru OK, Ong MK, Vangala S, Tseng CH, Rand CM, Humiston SG, Evans S, Sloyan M, Lerner C. Effect of Patient Portal Reminders Sent by a Health Care System on Influenza Vaccination Rates: A Randomized Clinical Trial. JAMA Intern Med. 2020 Jul 1;180(7):962-970. PMID: 32421168

Automated reminders for Influenza

Table 4.

Influenza Vaccination Rates by Study Group Overall and by Patient Subgroup at the End of the Study Including Self-reported Vaccinations

Subgroup	Patients who received an influenza vaccination, %				*P* value[a]
	0 Reminders	1 Reminder	2 Reminders	3 Reminders	
All patients	37.8	39.2	40.0	40.7	<.001
Age group, y					
0.5-17	52.3	51.9	54.4	53.1	.70
18- 64	32.4	34.1	34.8	35.5	<.001
≥65	53.6	54.6	55.1	56.7	<.001
Sex					
Female	37.9	39.1	39.8	40.5	<.001
Male	37.7	39.3	40.3	41.0	<.001
Race					
White	39.3	41.0	41.8	42.2	<.001
Black	31.1	32.9	33.1	36.0	.07
Asian	46.3	46.7	47.6	49.3	.007
Other or unknown	32.7	33.6	34.6	35.4	<.001
Ethnicity					
Hispanic	36.7	37.1	38.6	40.4	.02
Non-Hispanic or unknown	37.9	39.4	40.2	40.8	<.001

Accounting for the 35% that did not have the portal and assuming that this group has the same rate as the control, the overall benefit would be 39.7%

Szilagyi PG, Albertin C, Casillas A, Valderrama R, Duru OK, Ong MK, Vangala S, Tseng CH, Rand CM, Humiston SG, Evans S, Sloyan M, Lerner C. Effect of Patient Portal Reminders Sent by a Health Care System on Influenza Vaccination Rates: A Randomized Clinical Trial. JAMA Intern Med. 2020 Jul 1;180(7):962-970. PMID: 32421168

CDS to reduce polypharmacy

RESEARCH

Use of an electronic decision support tool to reduce polypharmacy in elderly people with chronic diseases: cluster randomised controlled trial

Anja Rieckert,[1] David Reeves,[2] Attila Altiner,[3] Eva Drewelow,[3] Aneez Esmail,[2] Maria Flamm,[4] Mark Hann,[5] Tim Johansson,[4] Renate Klaassen-Mielke,[6] Ilkka Kunnamo,[7] Christin Löffler,[3] Giuliano Piccoliori,[8] Christina Sommerauer,[1] Ulrike S Trampisch,[1] Anna Vögele,[9] Adrine Woodham,[2] Andreas Sönnichsen[2,10]

-Large RCT (N=3904)

-European, multinational

-2-year

Rieckert A, Reeves D, Altiner A, Drewelow E, Esmail A, Flamm M, Hann M, Johansson T, Klaassen-Mielke R, Kunnamo I, Löffler C, Piccoliori G, Sommerauer C, Trampisch US, Vögele A, Woodham A, Sönnichsen A. Use of an electronic decision support tool to reduce polypharmacy in elderly people with chronic diseases: cluster randomised controlled trial. BMJ. 2020 Jun 18;369:m1822. PMID: 32554566

CDS to reduce polypharmacy

Table 1 | Components of the computerised decision support tool for comprehensive drug review in people with polypharmacy for chronic diseases

Components	Data sources
Check of indications for current drugs	Evidence-Based Medicine Guidelines and evidence summary collection[13]
Measurement results (laboratory, anthropometric) with alerts	Evidence-Based Medicine Guidelines[13] and consensus of EBMeDS clinical editorial team[14]
Recommendations about amending current drugs based on best available evidence	EBMeDS evidence based rules and reminders.[15] Systematic reviews on drugs commonly prescribed to older people[6 16-21] EU(7)-PIM list[22]
Dosage adjustment in renal malfunction	RENBASE database[23]
Potentially harmful drug-drug interactions	INXBASE database[24]
Contraindications	Pharmacological literature and summary of medicinal product characteristics by European Medicines Agency[25]
Dose warnings	Pharmacological literature and product summaries approved by regulatory authorities
Possible adverse drug reactions (risk of bleeding, renal toxicity, risk of seizures, anticholinergic effects, constipation, orthostatism, QT prolongation, sedation, serotonergic effect)	RISKBASE database[26]

EbMeDS=evidence based medicine electronic decision support; EU(7)-PIM=European Union (7)-potentially inappropriate medications.

Rieckert A, Reeves D, Altiner A, Drewelow E, Esmail A, Flamm M, Hann M, Johansson T, Klaassen-Mielke R, Kunnamo I, Löffler C, Piccoliori G, Sommerauer C, Trampisch US, Vögele A, Woodham A, Sönnichsen A. Use of an electronic decision support tool to reduce polypharmacy in elderly people with chronic diseases: cluster randomised controlled trial. BMJ. 2020 Jun 18;369:m1822. PMID: 32554566

CDS to reduce polypharmacy

Table 3 | Primary and secondary outcomes at last follow-up

Outcomes	Decision support group		Control group		Adjusted comparison estimate (95% CI)	P value (sensitivities)
	No	Estimate*	No	Estimate*		
Primary outcome						
First unplanned hospital admission or death†	1953	997 (51.0%)	1951	1055 (54.1%)	OR: 0.88 (0.73 to 1.07)	0.19 (MI‡ 0.114)
Sensitivity: time to first unplanned hospital admission or death	1953	0.46 (0.01)§	1951	0.50 (0.01)§	HR: 0.93 (0.82 to 1.05)	0.24
Key secondary outcome						
Last recorded No of drugs	1953	10.12 (3.01)	1951	10.52 (2.94)	Coefficient¶: 0.95 (0.94 to 0.97)	<0.001 (MI<0.001) (BS<0.001)
Sensitivity: change in No of drugs from baseline	1953	−0.42 (2.16)	1951	0.06 (2.04)	MD: −0.45 (−0.63 to -0.26)	<0.001 (MI<0.001) (BS<0.001)
Other secondary outcomes						
Death†	1953	380 (19.5%)	1951	366 (18.8%)	OR: 1.01 (0.73 to 1.38)	0.96
Sensitivity: time to death	1953	0.11 (0.01)§	1951	0.12 (0.01) §	HR: 0.90 (0.71 to 1.13)	0.35
First unplanned hospital admission†	1953	945 (48.4%)	1951	990 (50.7%)	OR: 0.92 (0.76 to 1.10)	0.36
Sensitivity: time to hospital admission	1953	0.49 (0.01)§	1951	0.52 (0.01)§	HR: 0.95 (0.83 to 1.07)	0.38
No of unplanned hospital admission	1953	0.76 (1.24)	1951	0.87 (1.34)	IRR: 0.91(0.69 to 1.20)	0.51 (BS 0.351)
Duration of unplanned hospital admission (days)	1949	7.89 (17.43)	1948	8.47 (18.18)	IRR: 0.95 (0.67 to 1.35)	0.79 (BS 0.707)
No of falls over trial period	1798	0.50 (1.26)	1785	0.51 (1.24)	IRR: 1.08 (0.88 to 1.34)	0.44 (BS 0.287)
≥1 fractures during trial period	1953	59 (3.0%)	1951	45 (2.3%)	OR: 1.37 (0.87 to 2.16)	0.17
SF-12:						
Physical component score (0-100)	1223	36.73 (9.44)	1146	36.32 (9.11)	MD: 0.07 (-0.69 to 0.83)	0.85
Mental component score (0-100)	1224	46.66 (11.09)	1145	46.27 (11.18)	MD: 0.34 (-0.69 to 1.37)	0.52

OR=odds ratio; MI=multiple imputation; HR=hazard ratio; BS=bootstrap; MD=mean difference; IRR=incidence rate ratio.
*Mean (standard deviation) or number (%) unless otherwise indicated.
†Participants who dropped out were analysed as having reached the endpoint.
‡Participants who dropped out were analysed using multiple imputation.
§Estimated proportion (standard error) reaching endpoint by 24 months, from survivor function.
¶Coefficient represents the adjusted ratio of the number of prescribed drugs in participants assigned to electronic decision support versus those assigned to treatment as usual (control group).

Rieckert A, Reeves D, Altiner A, Drewelow E, Esmail A, Flamm M, Hann M, Johansson T, Klaassen-Mielke R, Kunnamo I, Löffler C, Piccoliori G, Sommerauer C, Trampisch US, Vögele A, Woodham A, Sönnichsen A. Use of an electronic decision support tool to reduce polypharmacy in elderly people with chronic diseases: cluster randomised controlled trial. BMJ. 2020 Jun 18;369:m1822. PMID: 32554566

CDS for Acute Kidney Injury (AKI)

RESEARCH

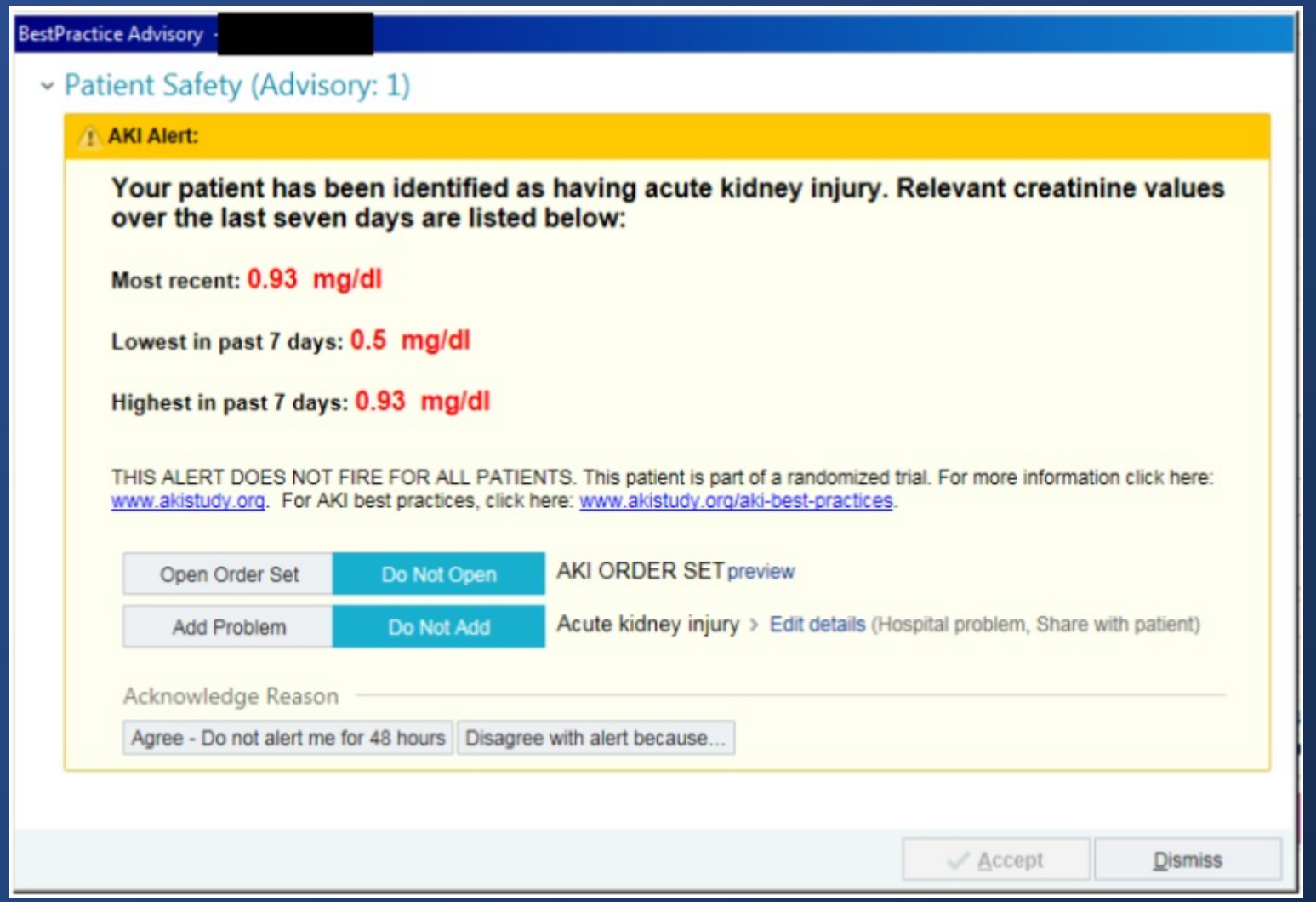
Electronic health record alerts for acute kidney injury: multicenter, randomized clinical trial

F Perry Wilson,[1,2] Melissa Martin,[1,2] Yu Yamamoto,[1,2] Caitlin Partridge,[3] Erica Moreira,[3] Tanima Arora,[1,2] Aditya Biswas,[1,2] Harold Feldman,[4] Amit X Garg,[5] Jason H Greenberg,[2,6] Monique Hinchcliff,[7] Stephen Latham,[8] Fan Li,[9] Haiqun Lin,[10] Sherry G Mansour,[1,2] Dennis G Moledina,[1,2] Paul M Palevsky,[11] Chirag R Parikh,[12] Michael Simonov,[2] Jeffrey Testani,[13] Ugochukwu Ugwuowo[1,2]

-N=6040
-US, 6 hospitals
-teaching & non-teaching

Wilson FP, Martin M, Yamamoto Y, Partridge C, Moreira E, Arora T, Biswas A, Feldman H, Garg AX, Greenberg JH, Hinchcliff M, Latham S, Li F, Lin H, Mansour SG, Moledina DG, Palevsky PM, Parikh CR, Simonov M, Testani J, Ugwuowo U. Electronic health record alerts for acute kidney injury: multicenter, randomized clinical trial. BMJ. 2021 Jan 18;372: PMID: 33461986

CDS for Acute Kidney Injury (AKI)



Wilson FP, Martin M, Yamamoto Y, Partridge C, Moreira E, Arora T, Biswas A, Feldman H, Garg AX, Greenberg JH, Hinchcliff M, Latham S, Li F, Lin H, Mansour SG, Moledina DG, Palevsky PM, Parikh CR, Simonov M, Testani J, Ugwuowo U. Electronic health record alerts for acute kidney injury: multicenter, randomized clinical trial. BMJ. 2021 Jan 18;372: PMID: 33461986

CDS for Acute Kidney Injury (AKI)

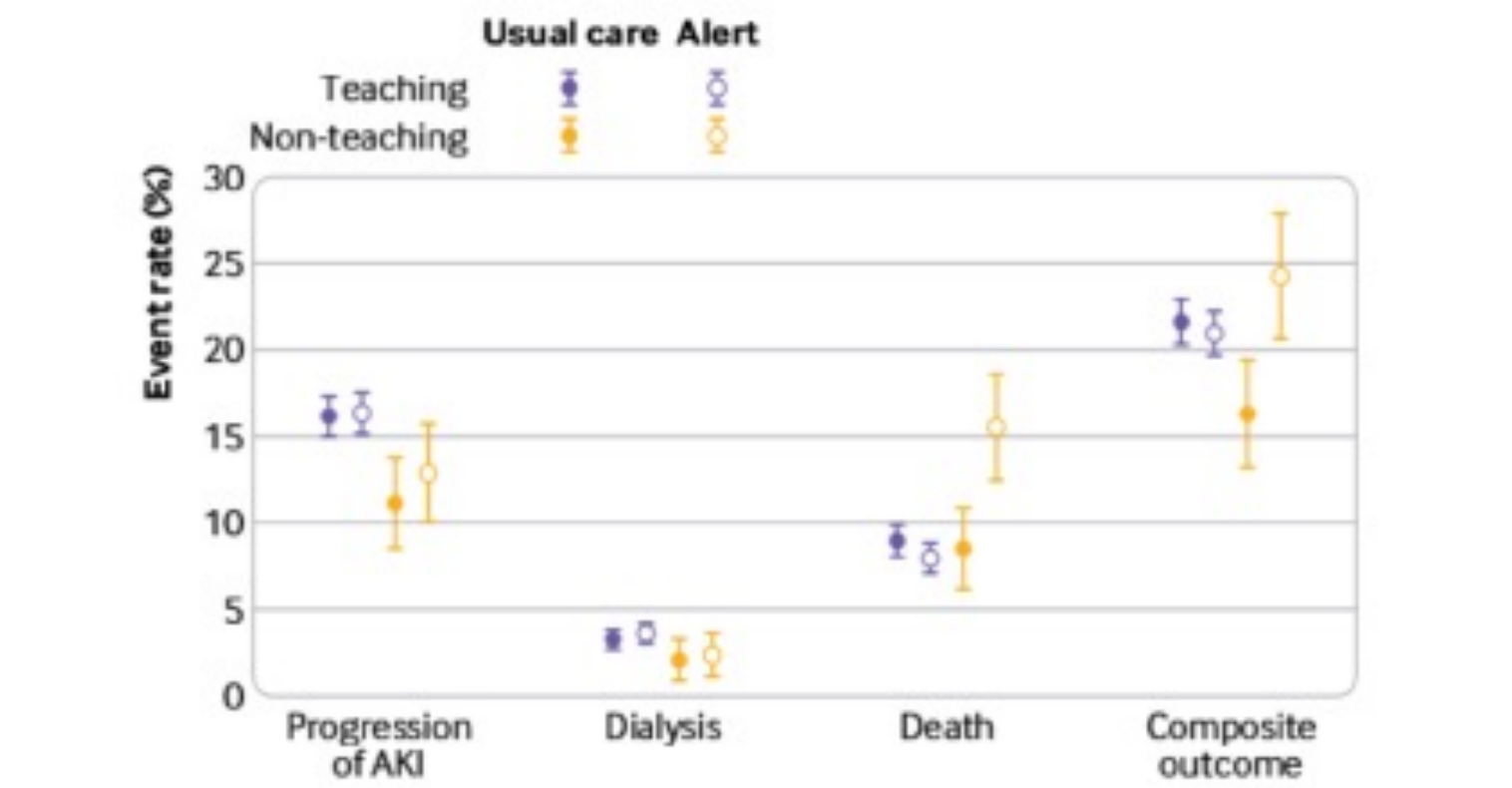


Fig 2 | Primary and secondary outcome events, stratified by hospital type. Error bars are 95% confidence intervals of the observed proportion of events. AKI=acute kidney injury

Wilson FP, Martin M, Yamamoto Y, Partridge C, Moreira E, Arora T, Biswas A, Feldman H, Garg AX, Greenberg JH, Hinchcliff M, Latham S, Li F, Lin H, Mansour SG, Moledina DG, Palevsky PM, Parikh CR, Simonov M, Testani J, Ugwuowo U. Electronic health record alerts for acute kidney injury: multicenter, randomized clinical trial. BMJ. 2021 Jan 18;372: PMID: 33461986

CDS for high cost imaging

PLOS ONE

RESEARCH ARTICLE

Clinical decision support for high-cost imaging: A randomized clinical trial

Joseph Doyle[1☯*], Sarah Abraham[2☯], Laura Feeney[3☯], Sarah Reimer[4☯], Amy Finkelstein[2☯]

1 Sloan School of Management, Massachusetts Institute of Technology, Cambridge, Massachusetts, United States of America, **2** Department of Economics, Massachusetts Institute of Technology, Cambridge, Massachusetts, United States of America, **3** Abdul Latif Jameel Poverty Action Lab, Department of Economics, Massachusetts Institute of Technology, Cambridge, Massachusetts, United States of America, **4** Aurora Health Care, Milwaukee, Wisconsin, United States of America

-Large RCT (N=3511 providers)

-American, multi-institution, single company

-1-year

-CDS with common EHR and common Imaging software

Doyle J, Abraham S, Feeney L, Reimer S, Finkelstein A. Clinical decision support for high-cost imaging: A randomized clinical trial. PLoS One. 2019 Mar 15;14(3):e0213373. doi: 10.1371/journal.pone.0213373. PMID: 30875381

CDS for high cost imaging

Table 2. Impact of CDS on scans.

	Control Group, Mean (SD) (n = 1,756)	CDS Group, Mean (SD) (n = 1,755)	Adjusted Between-Group Difference (95% CI)[a]	P-Value[a]
Outcome				
Targeted scans	17.0 (32.6)	15.3 (30.0)	-1.12 (-2.11 to -0.13)	0.027
CT scans[b]	10.5 (24.7)	9.8 (22.4)	-0.94 (-1.63 to -0.25)	0.008
MRI[b]	5.1 (13.5)	4.4 (14.1)	-0.11 (-0.60 to 0.39)	0.676
Red orders (scored 1–3)	5.9 (13.6)	5.3 (12.2)	-0.40 (-0.89 to 0.09)	0.110
Yellow orders (scored 4–6)	11.1 (23.0)	10.1 (20.9)	-0.76 (-1.48 to -0.04)	0.039
All High-cost scans	108.3 (188.7)	106.7 (179.3)	-1.74 (-5.90 to 2.42)	0.412
All Low-cost scans	370.1 (598.8)	333.3 (445.9)	-9.38 (-21.76 to 3.01)	0.138

Abbreviations: CDS, clinical decision support; CT, computed tomography; MRI, magnetic resonance imaging.

[a] Effect of CDS was estimated from a linear regression of the outcome on an indicator for whether the ordering provider was a treatment provider. All regressions include a control for the lag of the dependent variable; p-values and confidence intervals are based on heteroskedasticity-robust standard errors.

[b] Outcome not prespecified in trial registry.

Doyle J, Abraham S, Feeney L, Reimer S, Finkelstein A. Clinical decision support for high-cost imaging: A randomized clinical trial. PLoS One. 2019 Mar 15;14(3):e0213373. doi: 10.1371/journal.pone.0213373. PMID: 30875381

CDS for Diabetes Treatment

Heselmans *et al. Implementation Science* (2020) 15:5
https://doi.org/10.1186/s13012-019-0955-6

Implementation Science

RESEARCH Open Access

Computerized clinical decision support system for diabetes in primary care does not improve quality of care: a cluster-randomized controlled trial

Annemie Heselmans[1*], Nicolas Delvaux[1], Annouschka Laenen[1], Stijn Van de Velde[2], Dirk Ramaekers[3], Ilkka Kunnamo[4] and Bert Aertgeerts[1]

-Large RCT (51 practices, 120 physicians, 3815 patients)

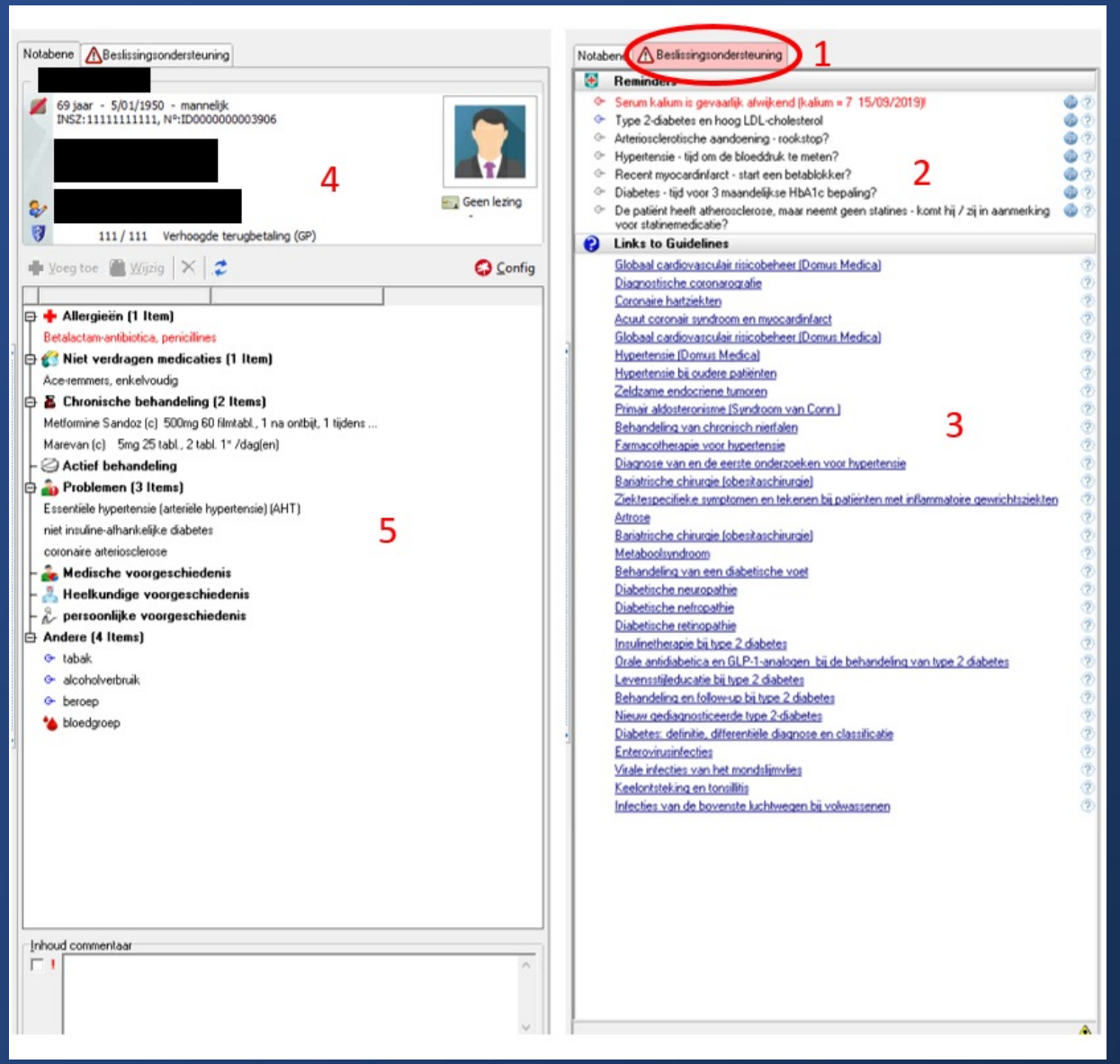
-Belgium

-1-year

-EHR Integrated CDS

Heselmans A, Delvaux N, Laenen A, Van de Velde S, Ramaekers D, Kunnamo I, Aertgeerts B. Computerized clinical decision support system for diabetes in primary care does not improve quality of care: a cluster-randomized controlled trial. Implement Sci. 2020 Jan 7;15(1):5. PMID: 31910877

CDS for Diabetes Treatment



Heselmans A, Delvaux N, Laenen A, Van de Velde S, Ramaekers D, Kunnamo I, Aertgeerts B. Computerized clinical decision support system for diabetes in primary care does not improve quality of care: a cluster-randomized controlled trial. Implement Sci. 2020 Jan 7;15(1):5. PMID: 31910877

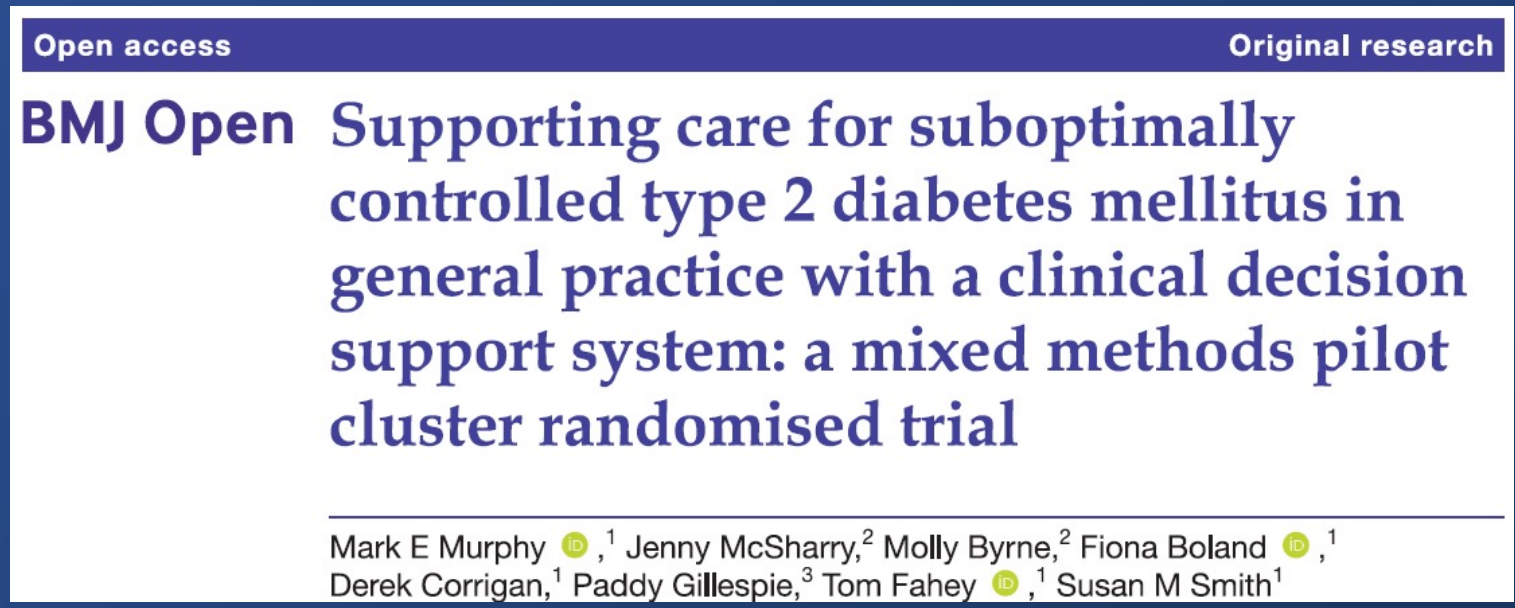
CDS for Diabetes Treatment

Table 5 Change differences between groups in a subgroup of patients with a mean HbA1c > 7%, a subgroup of patients with a mean LDL cholesterol > 100 mg/dL and a subgroup of patients with a mean blood pressure > 130/80 mg/dL

	Control Estimated mean (95% CI)	Intervention Estimated mean (95% CI)	Change difference IG-CG Estimated mean (95% CI)
HbA1c > 7%[1]			
Baseline (BL)	7.99 (7.65; 8.33)	8.27 (7.91; 8.63)	
6 months (6M)	7.78 (7.43; 8.14)	8.11 (7.73; 8.49)	
12 months (12M)	7.64 (7.31; 7.98)	7.53 (7.17; 7.89)	
Change BL–6M	−0.21 (−0.43; 0.02)	−0.16 (−0.42; 0.09)	0.04 (−0.29;0.38)
Change BL–12M	−0.35 (−0.54; −0.15)	−0.75 (−0.98; −0.51)	−0.40 (−0.70; −0.09)
Systolic blood pressure > 130 mmHg[2]			
Baseline	147.11 (144.67; 149.55)	147.77 (145.10; 150.44)	
6 months	143.75 (141.25; 146.25)	144.94 (142.10; 147.78)	
12 months	141.08 (138.56; 143.60)	141.68 (138.89; 144.47)	
Change BL–6M	−3.36 (−4.58; −2.14)	−2.83 (−4.50; −1.16)	0.53 (−1.54; 2.60)
Change BL–12M	−6.03 (-7.49; −4.57)	−6.09 (−7.89; −4.28)	0.06 (−2.39; 2.27)
LDL cholesterol > 100 mg/dL[4]			
Baseline	131.32 (128.29; 134.34)	128.84 (124.92; 132.77)	
6 months	126.88 (123.46; 130.31)	124.40 (119.93; 128.86)	
12 months	118.28 (114.73; 121.82)	115.94 (111.05; 120.82)	
Change BL–6M	−4.43 (−6.17; −2.69)	−4.44 (−6.89; −1.99)	−0.01 (−3.01; 2.99)
Change BL–12M	−13.04 (−15.64; −10.44)	−12.91 (−17.14; −8.67)	0.14 (-4.84;5.11)

Heselmans A, Delvaux N, Laenen A, Van de Velde S, Ramaekers D, Kunnamo I, Aertgeerts B. Computerized clinical decision support system for diabetes in primary care does not improve quality of care: a cluster-randomized controlled trial. Implement Sci. 2020 Jan 7;15(1):5. PMID: 31910877

CDS for Diabetes Treatment #2



Open access Original research

BMJ Open

Supporting care for suboptimally controlled type 2 diabetes mellitus in general practice with a clinical decision support system: a mixed methods pilot cluster randomised trial

Mark E Murphy ,[1] Jenny McSharry,[2] Molly Byrne,[2] Fiona Boland ,[1]
Derek Corrigan,[1] Paddy Gillespie,[3] Tom Fahey ,[1] Susan M Smith[1]

-RCT (14 practices, 134 patients)

-Ireland

-4-months

-Web-based CDS

Murphy ME, McSharry J, Byrne M, Boland F, Corrigan D, Gillespie P, Fahey T, Smith SM. Supporting care for suboptimally controlled type 2 diabetes mellitus in general practice with a clinical decision support system: a mixed methods pilot cluster randomised trial. BMJ Open. 2020 Feb 12;10(2):e032594.PMID: 32051304.

CDS for Diabetes Treatment #2

Summary of DECIDE Intervention

There are three specific components to the complex intervention, called DECIDE:

1. Training program/academic detailing of target GPs with the CDSS.
    - Behaviour change techniques (BCTs): credible source, demonstration of the behaviour, feedback on behaviour, instruction on how to perform the behaviour, behavioural practice/rehearsal and social support (unspecified).
2. Development of a remote 'finder tool' to help the GP and the practice nurse find patients with poor control.
    - BCTs: adding objects to the environment.
3. Development of a web-based CDSS, delivered as part of clinical workflow in Irish General Practice, with both the nurse and GP being able to use the system
    - BCTs: prompts/cues, credible source, adding objects to the environment.

Murphy ME, McSharry J, Byrne M, Boland F, Corrigan D, Gillespie P, Fahey T, Smith SM. Supporting care for suboptimally controlled type 2 diabetes mellitus in general practice with a clinical decision support system: a mixed methods pilot cluster randomised trial. BMJ Open. 2020 Feb 12;10(2):e032594.PMID: 32051304.

CDS for Diabetes Treatment #2

48 mmol/L = 6.5%

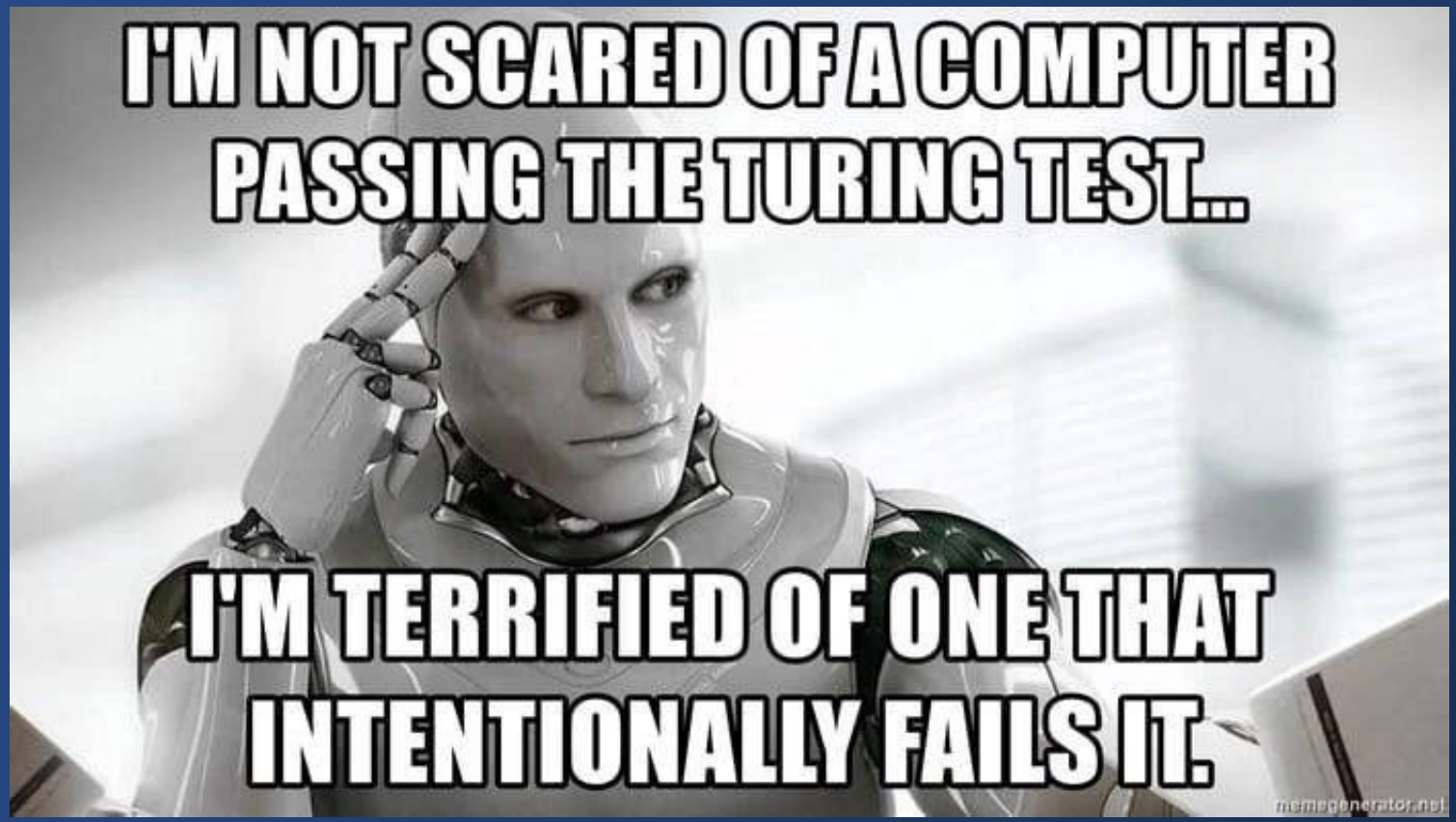
Table 4 Effect of the DECIDE intervention on HbA1c and secondary outcomes

	Baseline		Follow-up		PP*	ITT†	
	Mean (SD) intervention	Mean (SD) control	Mean (SD) intervention	Mean (SD) control	Mean difference (CI)	Mean difference (CI)	ICC
HbA1c (mmol/mol)							
Primary model (adjusted for baseline HbA1c)	83.4 (20.1)	79.0 (17.5)	69.0 (22.4)	70.8 (20.4)	−4.2 (−13.6 to 5.2)	−3.6 (−11.2 to 4.0)	0.100
Model 1 (adjusted for baseline HbA1c and insulin use)	-	-	-	-	−4.3 (−13.4 to 4.7)	−3.6 (−10.8 to 3.6)	0.073
Model 2 (adjusted for baseline HbA1c, insulin use and recency of testing‡)	-	-	-	-	−4.4 (−14.0 to 5.1)	−3.7 (−18.3 to 10.8)	0.084
SBP							
Primary model (adjusted for baseline SBP)	135.7 (20.7)	133.6 (15.7)	130.4 (22.4)	124.3 (23.3)	3.6 (−12.9 to 20.1)	4.2 (−11.3 to 20.1)	0.407
Model 1 (adjusted for baseline SBP and recency of testing‡)	-	-	-	-	0.0 (−8.9 to 8.9)	0.0 (−8.9 to 8.9)	0.014
Total cholesterol							
Primary model (adjusted for baseline total	4.7 (1.6)	4.8 (2.0)	4.5 (1.4)	4.0 (1.5)	0.4 (−0.2 to 0.9)	0.4 (−0.1 to 0.9)	0.003

Murphy ME, McSharry J, Byrne M, Boland F, Corrigan D, Gillespie P, Fahey T, Smith SM. Supporting care for suboptimally controlled type 2 diabetes mellitus in general practice with a clinical decision support system: a mixed methods pilot cluster randomised trial. BMJ Open. 2020 Feb 12;10(2):e032594.PMID: 32051304.

Transition Comedy Slide

AI topics by Colin

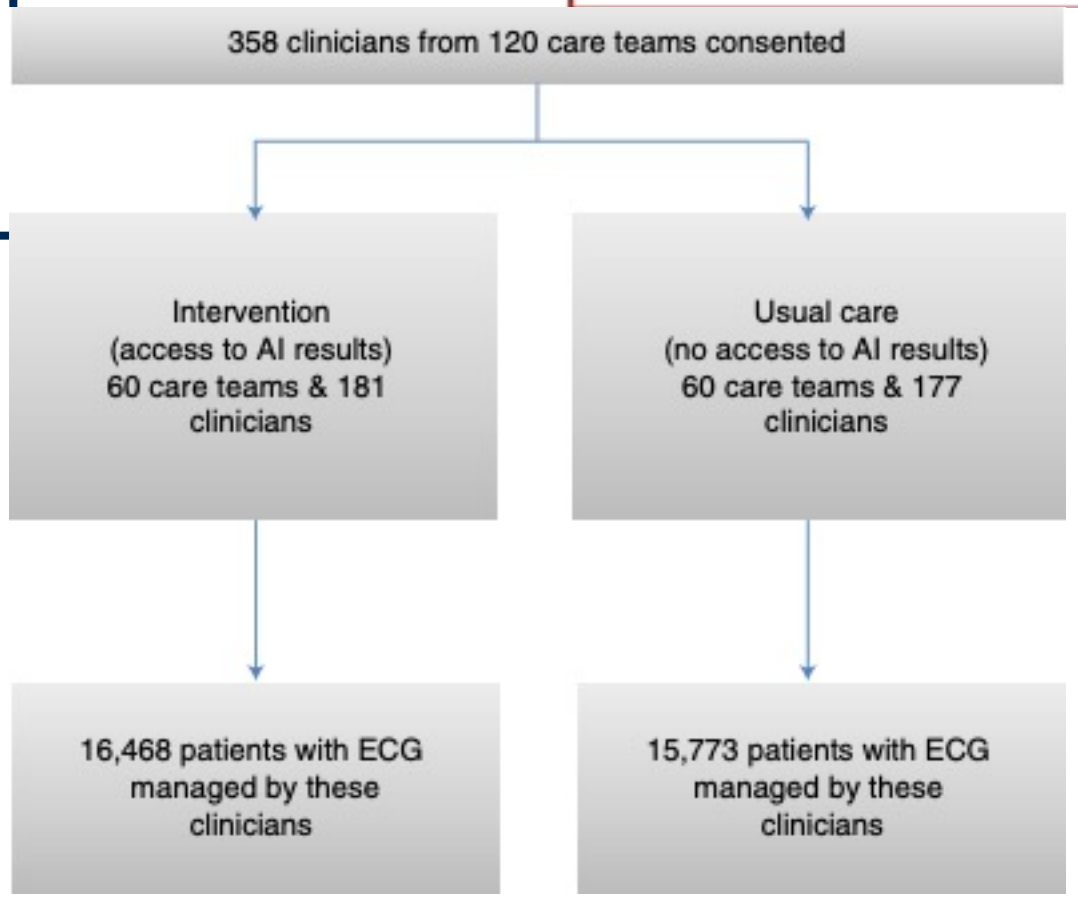


Artificial intelligence–enabled electrocardiograms for identification of patients with low ejection fraction: a pragmatic, randomized clinical trial

Xiaoxi Yao[1,2] ✉, David R. Rushlow[3], Jonathan W. Inselman[1], Rozalina G. McCoy[1,4], Thomas D. Thacher[3], Emma M. Behnken[5], Matthew E. Bernard[3], Steven L. Rosas[6], Abdulla Akfaly[7], Artika Misra[8], Paul E. Molling[9], Joseph S. Krien[10], Randy M. Foss[11], Barbara A. Barry[1], Konstantinos C. Siontis[2], Suraj Kapa[2], Patricia A. Pellikka[2], Francisco Lopez-Jimenez[2], Zachi I. Attia[2], Nilay D. Shah[1], Paul A. Friedman[2] and Peter A. Noseworthy[2]

nature medicine

- THEME – an increase in non-invasive data to assist in AI predictions
- This is an actual RCT (unlike most which are retrospective) which provided CDS in real time
- Low EF (<40%) is often asymptomatic and underdiagnosed
- AI did a good job in helping to predict patients who would benefit from an echo (increase in TTE and low EF)
- 95% of these patients ended up on B-blocker or ACE within 90 days (75% of these rx were new)



https://doi.org/10.1038/s41591-021-01335-4

ARTICLE OPEN

Prediction of short-term antidepressant response using probabilistic graphical models with replication across multiple drugs and treatment settings

Arjun P. Athreya[1], Tanja Brückl[2], Elisabeth B. Binder[2], A. John Rush[3,4,5], Joanna Biernacka[6], Mark A. Frye[7], Drew Neavin[8], Michelle Skime[7], Ditlev Monrad[9], Ravishankar K. Iyer[10], Taryn Mayes[11], Madhukar Trivedi[11], Rickey E. Carter[12], Liewei Wang[1], Richard M. Weinshilboum[1], Paul E. Croarkin[7] and William V. Bobo[13]

Can we predict SSRI efficiency earlier in order to prevent treatment failures or frequent medication changes

We then used unsupervised machine learning to identify specific depressive symptoms and thresholds of improvement that were predictive of antidepressant response by 4 weeks for a patient to achieve remission, response, or nonresponse by 8 weeks

It worked

Non-invasive vocal biomarker is associated with pulmonary hypertension

Jaskanwal Deep Singh Sara, Elad Maor, Barry Borlaug, Bradley R. Lewis, Diana Orbelo, Lliach O. Lerman, Amir Lerman

Published: April 16, 2020 • https://doi.org/10.1371/journal.pone.0231441

PLOS ONE

Vocal Biomarkers

- Pitch / Jitter / Frequency / etc

Dataset from “Vocalis” Israel (access to call center)

Associations previously established with CAD and CHF Hospitalizations

This study associates vocal biomarkers with Pulm Artery Pressures with success (looking to correlated PA pressures >40mgHg)

These results may have important practical clinical implications for telemedicine and remote monitoring of patients with heart failure and PH.

QUARTZ

- Only 30% of Radiologists report using some form of AI in 2020
- 40 of the more than 80 radiology algorithms currently cleared by the FDA, along with 27 in-house tools, were utilized by respondents.
  - Only 34% of these were used for image interpretation;
  - the other applications included work list management, image enhancement, operations, and measurements.

- The bottom line: only about 11% of radiologists used AI for image interpretation in a clinical practice. Of those not using AI, 72% have no plans to do so while approximately 20% want to adopt within five years.

https://qz.com/2016153/ai-promised-to-revolutionize-radiology-but-so-far-its-failing/?utm_content=buffer8ba02&utm_medium=social&utm_source=twitter.com&utm_campaign=buffer

AI and Rads

The reason for this slow diffusion is poor performance. Only 5.7% of the users reported that AI always works while 94% reported inconsistent performance.

*"When we collect data from Stanford Hospital, then we train and test on data from the same hospital, indeed, we can publish papers showing [the algorithms] are comparable to human radiologists in spotting certain conditions. It turns out [that when] you take that same model, that same AI system, to an older hospital down the street, with an older machine, and the technician uses a slightly different imaging protocol, that data drifts to cause the performance of AI system to degrade significantly. In contrast, any human radiologist can walk down the street to the older hospital and do just fine. So even though at a moment in time, on a specific data set, we can show this works, the clinical reality is that these models still need a lot of work to reach production....**All of AI, not just healthcare, has a proof-of-concept-to-production gap**"*

https://qz.com/2016153/ai-promised-to-revolutionize-radiology-but-so-far-its-failing/?utm_content=buffer8ba02&utm_medium=social&utm_source=twitter.com&utm_campaign=buffer

AMIA Position Paper

Recommendations for the safe, effective use of adaptive CDS in the US healthcare system: an AMIA position paper

Carolyn Petersen [1], Jeffery Smith [2], Robert R. Freimuth [3], Kenneth W. Goodman [4], Gretchen Purcell Jackson [5,6], Joseph Kannry [7], Hongfang Liu [8], Subha Madhavan [9], Dean F. Sittig [10], and Adam Wright [11]

2 forms of Adaptive CDS (ACDS) – Marketed and Self-Developed

Adaptive CDS differs from static in that it has capacity to learn from data and modify recommendations based on those data

Recommendations follow the FDA – Software as a Medical Device (SaMD) pathway

Key questions?

- How do we validate the algorithms? Re-validate over time? Data to train them ?
    - Indications? Contraindications? Warnings?
- What key regulatory bodies need to be involved (FDA / CMS / ONC/ HHS / etc.)?
- Reporting requirements?
- How do we train users (physicians are not engineers….)?

Adaptive CDS – AMIA Position

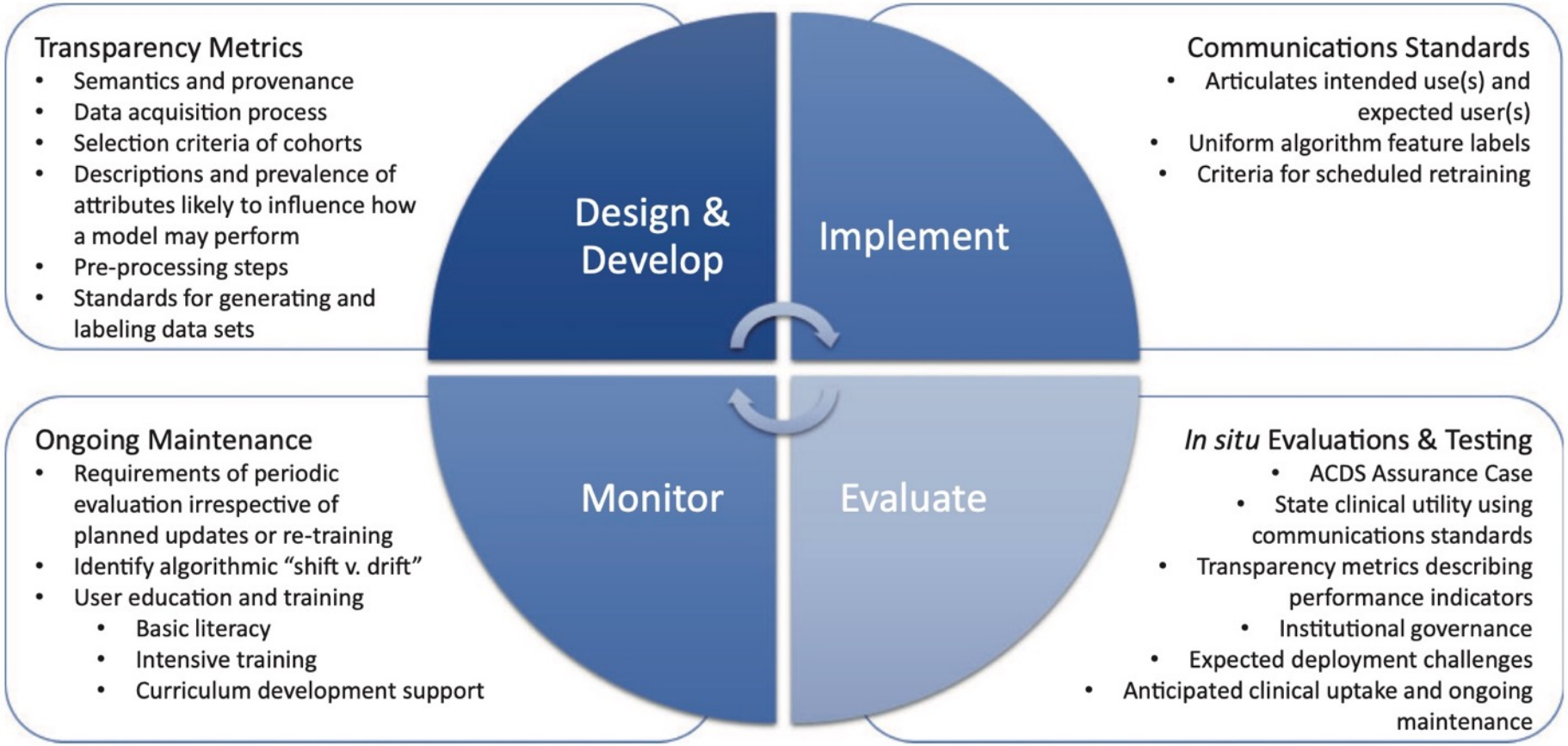


Figure 1. Policy recommendations for all stages of Adaptive CDS (ACDS)—design and development, implementation, evaluation, and ongoing monitoring—require further development to ensure safe and effective ACDS. A concerted multistakeholder effort to identify key transparency metrics for training datasets and communications standards for AI-driven applications in healthcare is needed to understand how bias can corrupt AI-driven decision support and identify ways to mitigate such bias. Additionally, policies that standardize *in situ* testing and evaluation, as well as ongoing maintenance, of ACDS should be established.

Imaging Assistance; AI guided colonoscopy

Gastroenterology 2020;159:512–520

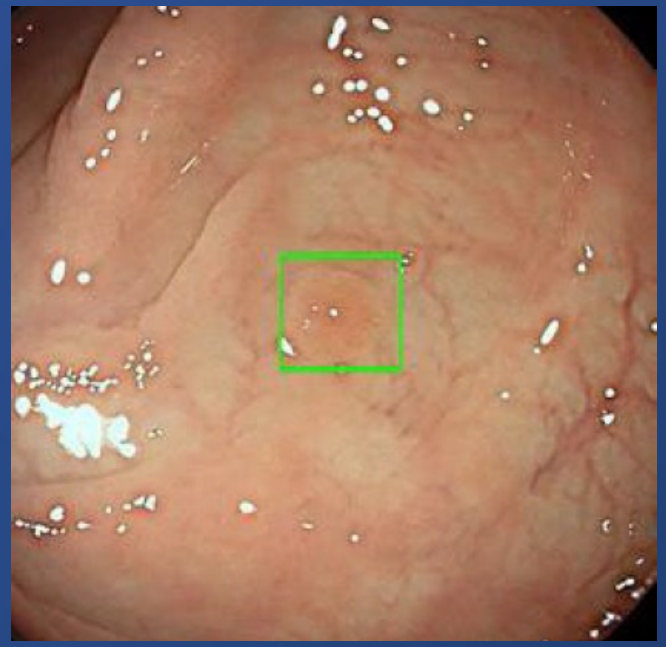
Efficacy of Real-Time Computer-Aided Detection of Colorectal Neoplasia in a Randomized Trial

Alessandro Repici,[1] Matteo Badalamenti,[1] Roberta Maselli,[1] Loredana Correale,[1] Franco Radaelli,[2] Emanuele Rondonotti,[2] Elisa Ferrara,[1] Marco Spadaccini,[1] Asma Alkandari,[3] Alessandro Fugazza,[1] Andrea Anderloni,[1] Piera Alessia Galtieri,[1] Gaia Pellegatta,[1] Silvia Carrara,[1] Milena Di Leo,[1] Vincenzo Craviotto,[1] Laura Lamonaca,[1] Roberto Lorenzetti,[4] Alida Andrealli,[2] Giulio Antonelli,[4] Michael Wallace,[5] Prateek Sharma,[6] Thomas Rosch,[7] and Cesare Hassan[4]

-RCT (3 practices, 700 patients)
-Italy
-Single Intervention, no F/U
-Not blinded
-6 gastroenterologists

Repici A, Badalamenti M, Maselli R, Correale L, Radaelli F, Rondonotti E, Ferrara E, Spadaccini M, Alkandari A, Fugazza A, Anderloni A, Galtieri PA, Pellegatta G, Carrara S, Di Leo M, Craviotto V, Lamonaca L, Lorenzetti R, Andrealli A, Antonelli G, Wallace M, Sharma P, Rosch T, Hassan C. Efficacy of Real-Time Computer-Aided Detection of Colorectal Neoplasia in a Randomized Trial. Gastroenterology. 2020 Aug;159(2):512-520.e7 Epub 2020 May 1. PMID: 32371116.

AI (CNN) guided colonoscopy
(Production of CNN)



-Series of videos of 2684 histologically confirmed polyps.
-840 patients
-1.5 million images extracted and manually annotated by expert endoscopists.

-Method: Convoluted Neural Network
-training & validation cohorts

-Sensitivity was 99.7%
-False-Positive rate was < 1%

-Details otherwise not given (for profit, device funding)

GI-Genius®, Medtronic

Hassan C, Wallace MB, Sharma P, Maselli R, Craviotto V, Spadaccini M, Repici A. New artificial intelligence system: first validation study versus experienced endoscopists for colorectal polyp detection. Gut. 2020 May;69(5):799-800. doi: 10.1136/gutjnl-2019-319914. Epub 2019 Oct 15. PMID: 31615835.

AI (CNN) guided colonoscopy

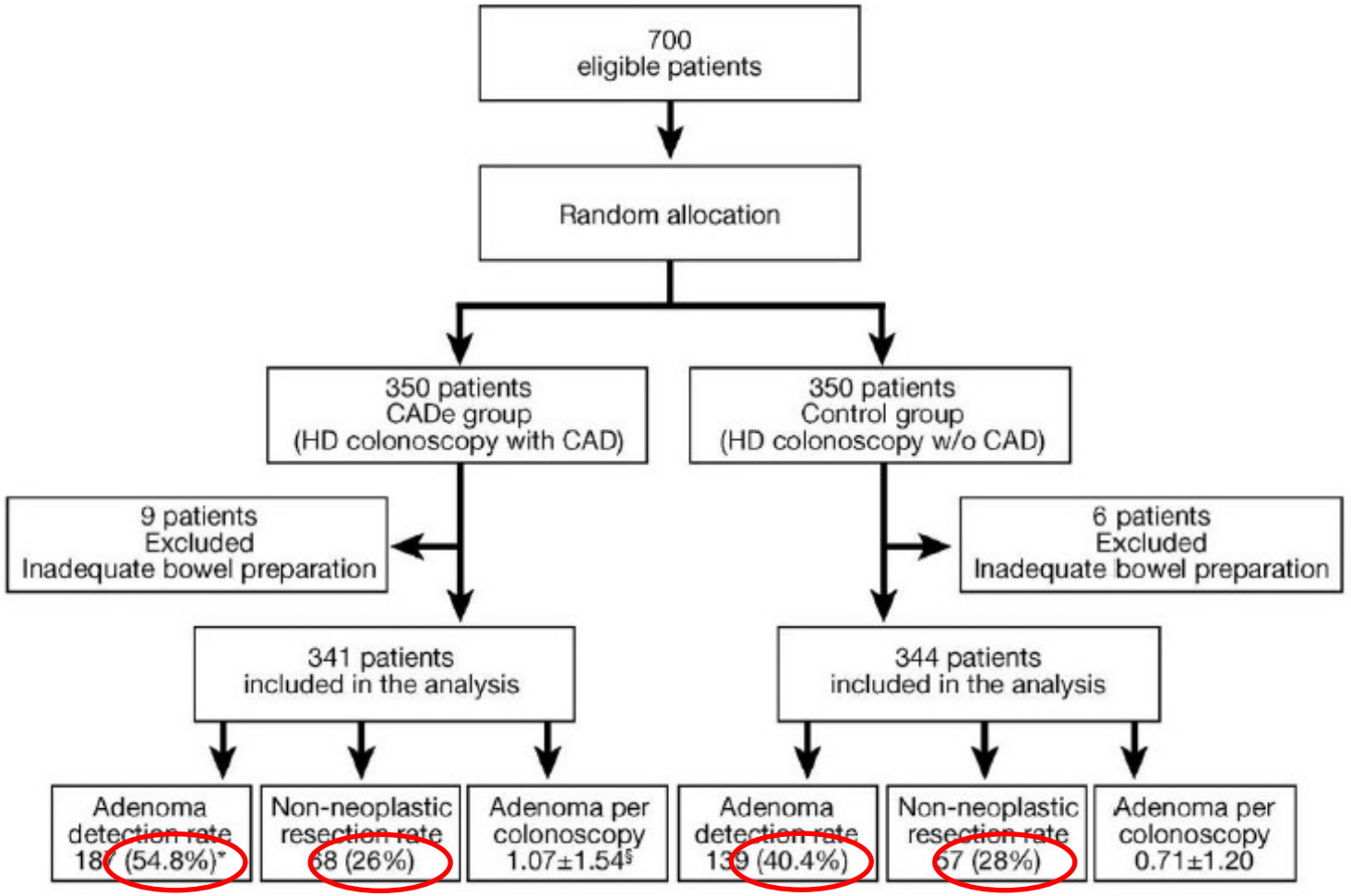
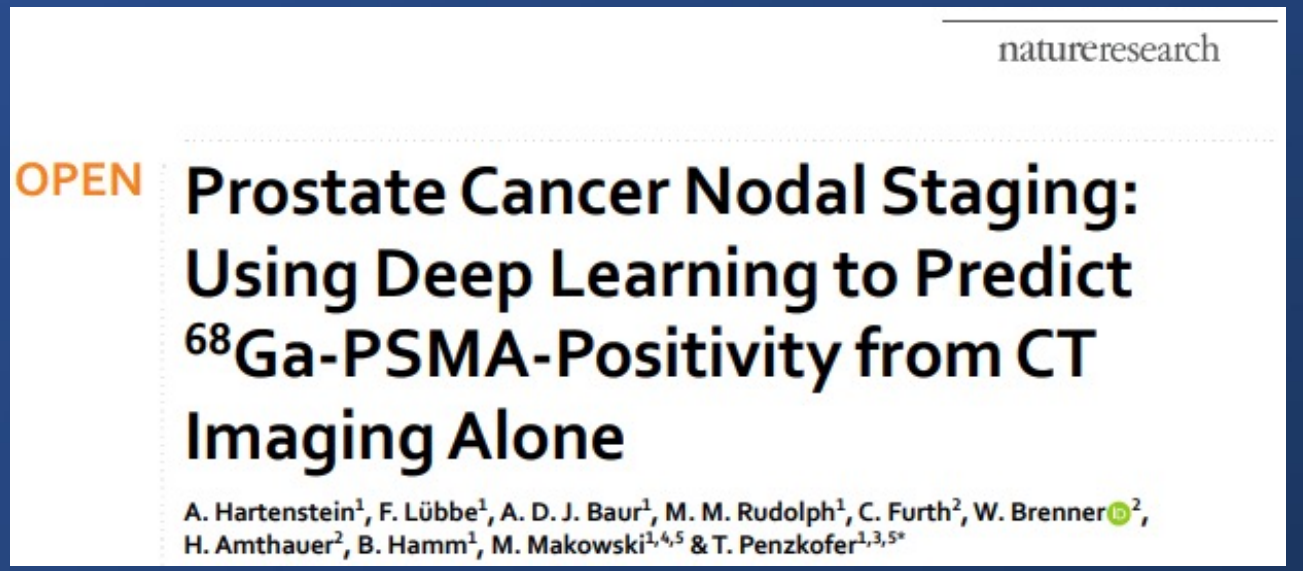


Figure 2. Study flow chart including clinical outcomes. *1.30 (95% CI, 1.14-1.45). §Incidence Rate Ratio 1.46 (95% CI, 1.15-1.86).

Repici A, Badalamenti M, Maselli R, Correale L, Radaelli F, Rondonotti E, Ferrara E, Spadaccini M, Alkandari A, Fugazza A, Anderloni A, Galtieri PA, Pellegatta G, Carrara S, Di Leo M, Craviotto V, Lamonaca L, Lorenzetti R, Andrealli A, Antonelli G, Wallace M, Sharma P, Rosch T, Hassan C. Efficacy of Real-Time Computer-Aided Detection of Colorectal Neoplasia in a Randomized Trial. Gastroenterology. 2020 Aug;159(2):512-520.e7 Epub 2020 May 1. PMID: 32371116.

Example of a retrospective "typical" AI Study

Convoluted Neural Network learning from CT scans for prostate CA



nature research

OPEN

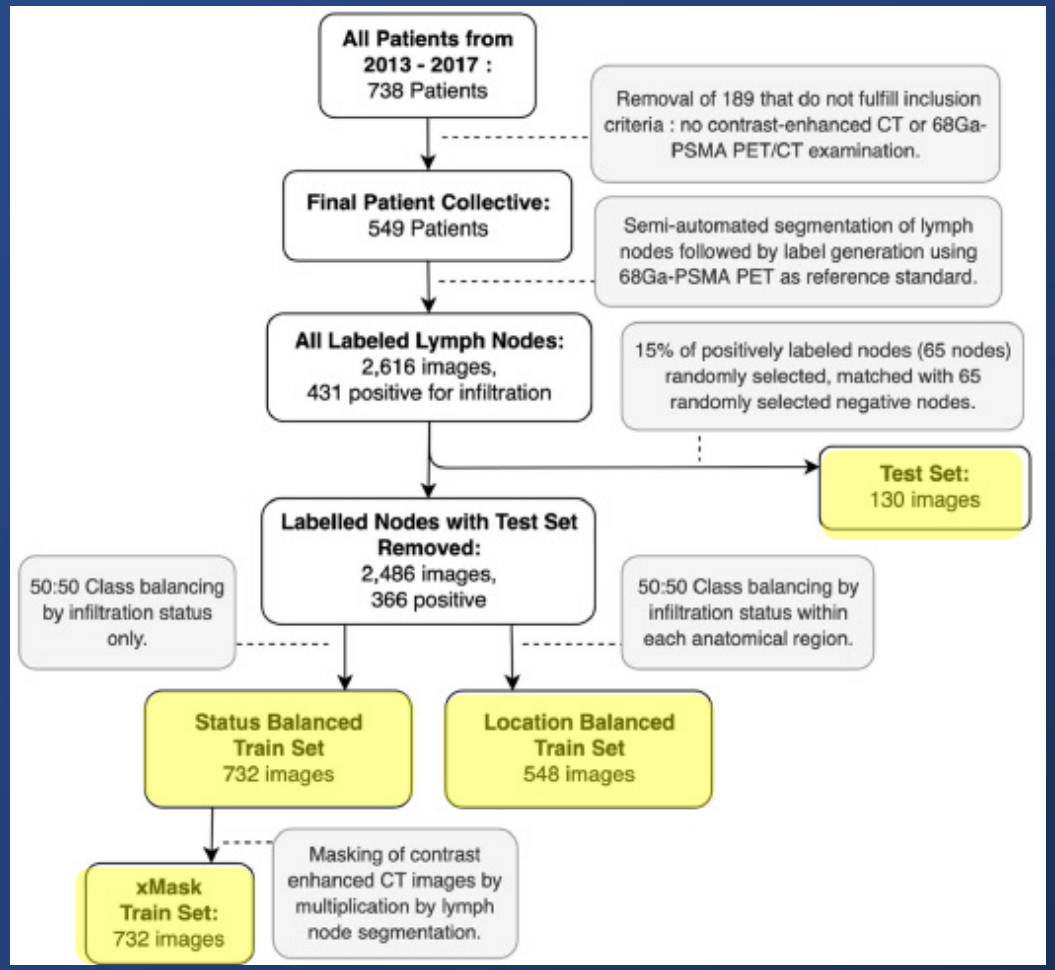
Prostate Cancer Nodal Staging: Using Deep Learning to Predict ^{68}Ga-PSMA-Positivity from CT Imaging Alone

A. Hartenstein[1], F. Lübbe[1], A. D. J. Baur[1], M. M. Rudolph[1], C. Furth[2], W. Brenner[2], H. Amthauer[2], B. Hamm[1], M. Makowski[1,4,5] & T. Penzkofer[1,3,5*]

-? Practice sites
-Germany
-2 Uroradiologists

Hartenstein A, Lübbe F, Baur ADJ, Rudolph MM, Furth C, Brenner W, Amthauer H, Hamm B, Makowski M, Penzkofer T. Prostate Cancer Nodal Staging: Using Deep Learning to Predict 68Ga-PSMA-Positivity from CT Imaging Alone. Sci Rep. 2020 Feb 25;10(1):3398. doi: 10.1038/s41598-020-60311-z. PMID: 32099001; PMCID: PMC7042227.

CNN learning from CT scans for prostate CA



Hartenstein A, Lübbe F, Baur ADJ, Rudolph MM, Furth C, Brenner W, Amthauer H, Hamm B, Makowski M, Penzkofer T. Prostate Cancer Nodal Staging: Using Deep Learning to Predict 68Ga-PSMA-Positivity from CT Imaging Alone. Sci Rep. 2020 Feb 25;10(1):3398. doi: 10.1038/s41598-020-60311-z. PMID: 32099001; PMCID: PMC7042227.

CNN learning from CT scans for prostate CA

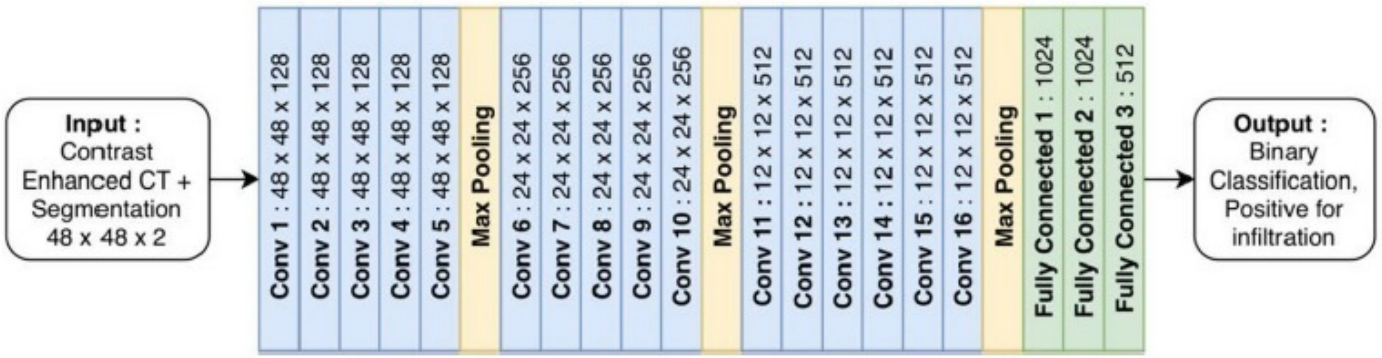
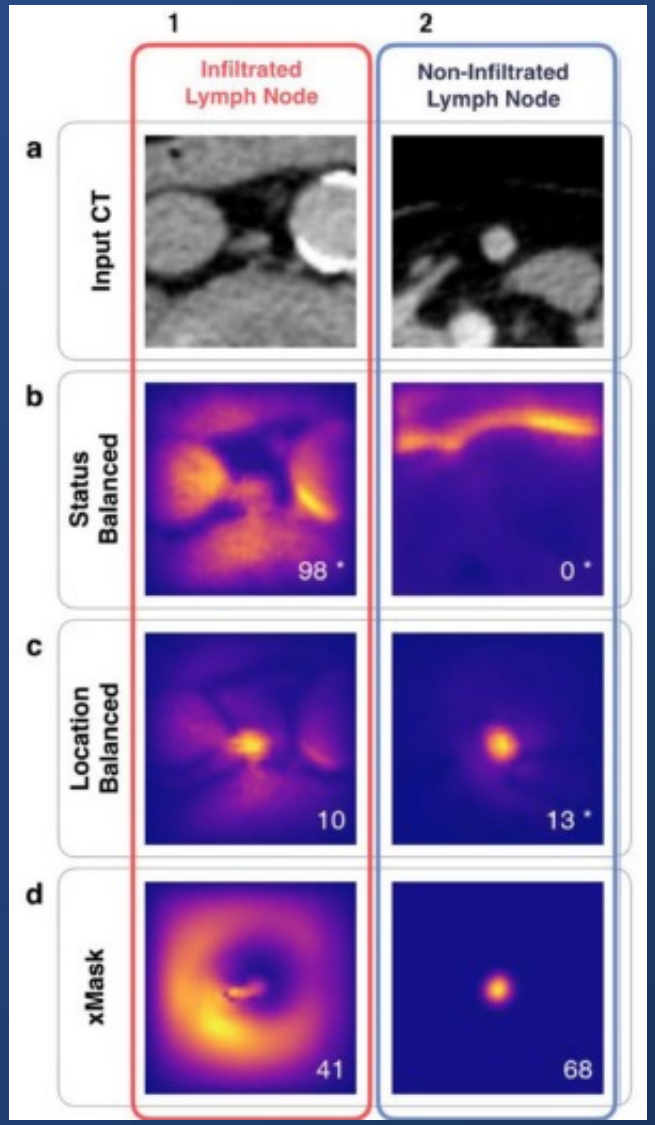


Figure 4. Convolutional neural network architecture. All three CNNs developed shared a common architecture and differed by the data used for training. CNNs received 2D contrast-enhanced CT images and segmentation masks as input, with input images augmented randomly during training. All convolutional layers used a kernel size of 3×3. A rectified linear unit (ReLU) activation function followed by batch normalization was performed at every layer. Adam optimization was used to update network weights, with parameters for alpha, beta1, beta2 and epsilon set at 0.0001, 0.9, 0.999 and 1e-08. Training was continued for 50 epochs.

This is mainly for Colin, obvious to us, be he has no intuition with neural network architecture…

Hartenstein A, Lübbe F, Baur ADJ, Rudolph MM, Furth C, Brenner W, Amthauer H, Hamm B, Makowski M, Penzkofer T. Prostate Cancer Nodal Staging: Using Deep Learning to Predict 68Ga-PSMA-Positivity from CT Imaging Alone. Sci Rep. 2020 Feb 25;10(1):3398. doi: 10.1038/s41598-020-60311-z. PMID: 32099001; PMCID: PMC7042227.

The Heat Map



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CNN learning from CT scans for prostate CA

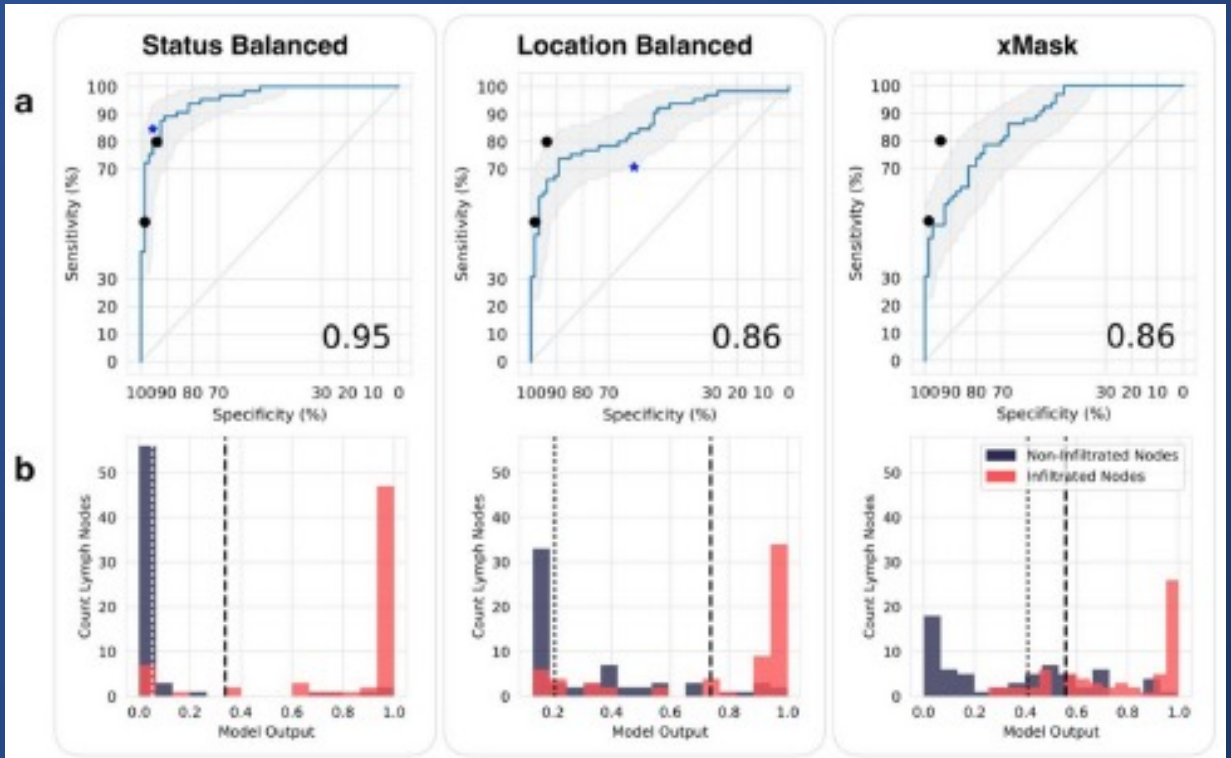


Figure 5. Classification performance. (**a**) Shown are the ROC curves for the three trained CNNs on the separate test set (n = 130) with 95% confidence interval of the sensitivity at given specificities in shaded gray. Displayed in the lower right hand corner is the corresponding AUC. Classification by individual radiologists on the same test set are displayed as black dots. Blue stars show random forest performance on the separate test set using the corresponding training dataset (status or location balanced). (**b**) Histograms of CNN model classification performance on the test set. The threshold that maximizes Youden's index is shown as a dashed line. The threshold which corresponds to a 90% sensitivity is shown as a dotted line. Infiltrated nodes (red bars) to the right of the given threshold are 'true positive', while those to the left are 'false negative': non-infiltrated nodes (blue) to the left are true negative, to the right are false positive.

2 experienced uroradiologists

AUC_1=0.81
AUC_2=0.75

Hartenstein A, Lübbe F, Baur ADJ, Rudolph MM, Furth C, Brenner W, Amthauer H, Hamm B, Makowski M, Penzkofer T. Prostate Cancer Nodal Staging: Using Deep Learning to Predict 68Ga-PSMA-Positivity from CT Imaging Alone. Sci Rep. 2020 Feb 25;10(1):3398. doi: 10.1038/s41598-020-60311-z. PMID: 32099001; PMCID: PMC7042227.

Transition Comedy Slide

Safe Order Entry by Bill

- Retract and Reorder oh my

Self Promotion: Analysis of Inpatient Voiding

Journal of the American Medical Informatics Association, 28(1), 2021, 86–94
doi: 10.1093/jamia/ocaa264
Advance Access Publication Date: 22 November 2020
Research and Applications

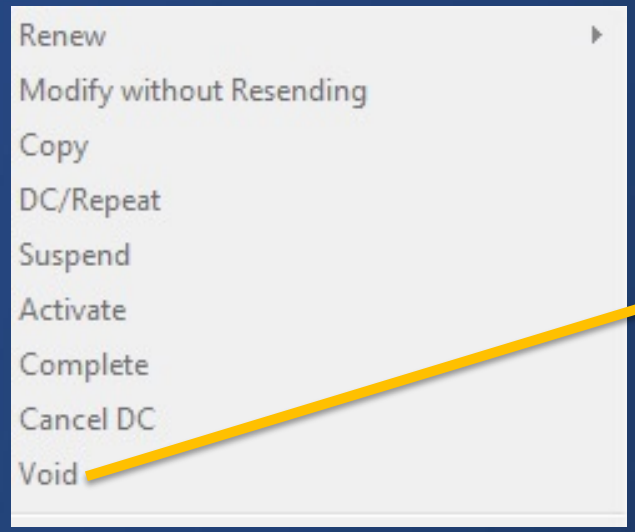
AMIA

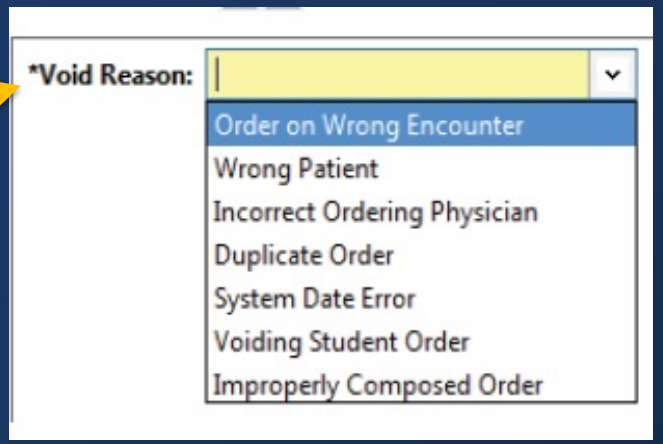
OXFORD

Research and Applications

Risk factors associated with medication ordering errors

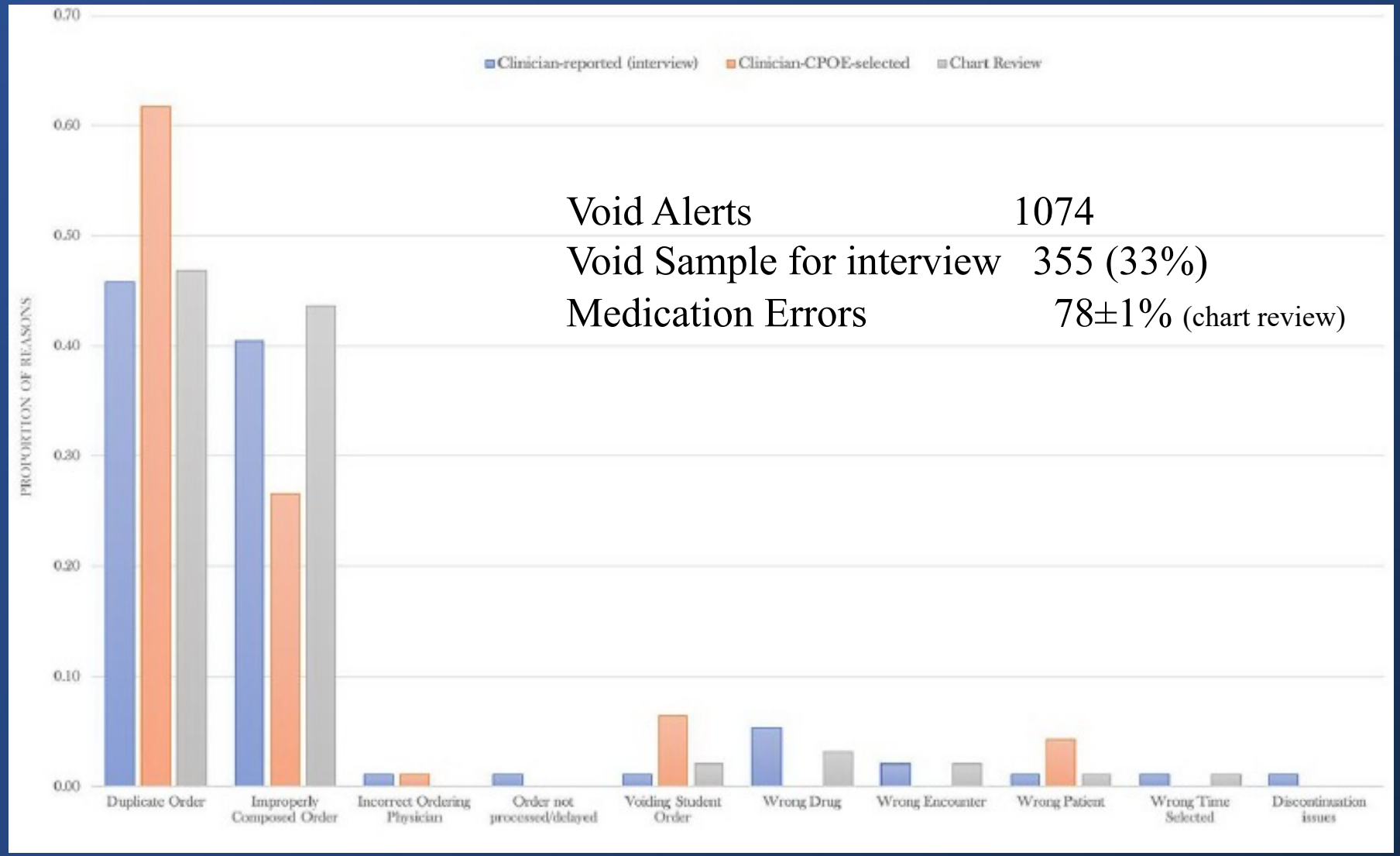
Joanna Abraham [1,2], William L. Galanter[3,4], Daniel Touchette[4], Yinglin Xia[3], Katherine J. Holzer[1], Vania Leung[3], and Thomas Kannampallil [1,2]





Abraham J, Galanter WL, Touchette D, Xia Y, Holzer KJ, Leung V, Kannampallil T. Risk factors associated with medication ordering errors. J Am Med Inform Assoc. 2021 Jan 15;28(1):86-94. PMID: 33221852

Analysis of Inpatient Voiding



Void Alerts	1074
Void Sample for interview	355 (33%)
Medication Errors	78±1% (chart review)

Reasons for computerised provider order entry (CPOE)-based inpatient medication ordering errors: an observational study of voided orders. BMJ Qual Saf. 2018 Apr;27(4):299-307 PMID: 28698381

Analysis of Inpatient Voiding

Table 3, Systems Engineering Initiative for Patient Safety–based risk factors associated with each type of medication ordering error

	Technological factors	Cognitive factors	Social factors	Environmental factors	Organizational factors
Duplicate order	0.40	0.23	0.24	0.09	0.04
Wrong drug	0.30	0.48	0.00	0.12	0.10
Wrong encounter	0.50	0.00	0.50	0.00	0.00
Wrong patient	0.19	0.51	0.01	0.18	0.11
wrong route/dose/schedule/strength	0.29	0.36	0.10	0.12	0.13
Not clinically appropriate	0.40	0.20	0.33	0.00	0.07
Other	0.43	0.19	0.19	0.06	0.13

Each cell shows the proportion of the contribution of each risk factor for a medication error type.

Abraham J, Galanter WL, Touchette D, Xia Y, Holzer KJ, Leung V, Kannampallil T. Risk factors associated with medication ordering errors. J Am Med Inform Assoc. 2021 Jan 15;28(1):86-94. PMID: 33221852

Analysis of Inpatient Voiding

Technologic Risk Factors: *CPOE usability issues* (38%), *CPOE interface design* (16% of clinician-reported technological risk factors) and CDS alert design issues (12%), and *limited CPOE training and experience* (16%)

Cognitive Risk Factor: *multitasking* (15%) and alert fatigue (10%), other distinct risk factors included *clinician negligence* (29%), misinterpretation of *verbal orders* (4%), and mix-up of patient charts (6%)

Social risk factors: communication gaps among clinicians (53% of social risk factors) and between clinicians and patients or their caregivers (47%).

Environmental risk factors: *interruptions* (42% of environmental risk factors), *distractions* (30%), *noise* (14 %), and time constraints within the environmental context (2%)

Organization risk factors: *high clinician workload* (61 % of organizational risk factors), *staffing issues* (14%), limited protocol awareness (11 %), and protocol violations (10%)

Abraham J, Galanter WL, Touchette D, Xia Y, Holzer KJ, Leung V, Kannampallil T. Risk factors associated with medication ordering errors. J Am Med Inform Assoc. 2021 Jan 15;28(1):86-94. PMID: 33221852

Clinician Reported Mitigation Strategies (as a reference)

Table 4. Clinician-reported strategies for mitigating medication ordering errors and their risk factors

Duplicate ordering errors	
Clinician level	• Review medication lists prior to ordering (prompt to review) • Refresh order entry page before finalizing orders
CPOE-CDS level	• Prevent easy chart flipping • Improve wording of CDS alerts and order sets • Create "true" duplicate alerts and review prompts • Update CPOE instantly to minimize lag time • Block simultaneous order entries by multiple clinicians • Allow clinicians to modify order sets and highlight duplicates with order sets/individual orders • Generate and run ordering report for patient at time of ordering • Organize medication summary more clearly to increase readability • Increase visibility of order set medications
Unit and organizational level	• Increase training and orientation on eMAR and CPOE shortcuts and menu options as well as on drug ordering policies, common drugs, and ordering workflow within CPOE (especially for interns), and offer ongoing enrichment classes • Minimize or eliminate verbal orders • Implement standardized communication protocols • Increase number of providers (eg, interns) in practice

Abraham J, Galanter WL, Touchette D, Xia Y, Holzer KJ, Leung V, Kannampallil T. Risk factors associated with medication ordering errors. J Am Med Inform Assoc. 2021 Jan 15;28(1):86-94. PMID: 33221852

Clinician Reported Mitigation Strategies (as a reference)

Wrong dose/route/strength	
Clinician level	• Allow access to home medication list
	• Review and verify special orders
CPOE-CDS level	• Limit order options based on current medication availabilities at pharmacies
	• Create presaved order sets for future access (including for special unit orders)
	• Show all applicable order routes at time of ordering
	• Improve interoperability between eMAR and CPOE
	• Create concise order sentences in CPOE
	• Color-code medication routes
	• Design flags for one-time orders vs continued orders
	• Set reminder pop-ups on specific types of dosages
	• Create customizable alerts based on clinician ordering behaviors/contextual patterns
	• Develop a CPOE-based error recognition/prediction system to alert clinicians of potential common ordering mistakes (eg, pharmacy decision support)
	• Condense all order information on one tab to minimize clicks and tab switching
	• Update search feature on orders
	• Automatically cross-reference insurance policies with medication options
	• Automatically calculate medication costs before ordering
Unit and organizational level	• Increase training and orientation on drug ordering policies, common drugs, and ordering workflow within CPOE (especially for interns)
	• Develop a formal communication channel between provider and pharmacist via CPOE to place correct order
	• Add a required protocol step to check medication and dosing before ordering

Abraham J, Galanter WL, Touchette D, Xia Y, Holzer KJ, Leung V, Kannampallil T. Risk factors associated with medication ordering errors. J Am Med Inform Assoc. 2021 Jan 15;28(1):86-94. PMID: 33221852

Clinician Reported Mitigation Strategies (as a reference)

Wrong patient	
Clinician level	• Read the patient first and last name and double-check the chart at time of ordering • Review the order entry before signing
CPOE-CDS level	• Make patient name noticeable on order page (color, italics) • Allow clicking of only relevant ordering options • Use additional patient identifiers (first and last name, location, problem lists, etc.) when communicating verbal orders
Unit and organizational level	• Increase training on eMAR
Wrong drug	
Clinician level	• Communicate with patient about preferences prior to medication reconciliation • Set up fatigue protocol to review actions for errors • Include medication indication checklist for handoffs • Review medication list at time of ordering
CPOE-CDS level	• Display primary care provider and patient-preferred pharmacy at time of ordering
Unit and organizational level	• Wait to place postoperative orders after patient admission to postoperative units • Improve protocol on time management and task attentiveness • Training on protocols for special medications (opioids, brain toxic meds, methadone program)
Wrong encounter	
CPOE-CDS level	• Label encounters to be more noticeable on display

Abraham J, Galanter WL, Touchette D, Xia Y, Holzer KJ, Leung V, Kannampallil T. Risk factors associated with medication ordering errors. J Am Med Inform Assoc. 2021 Jan 15;28(1):86-94. PMID: 33221852

Patient Pictures

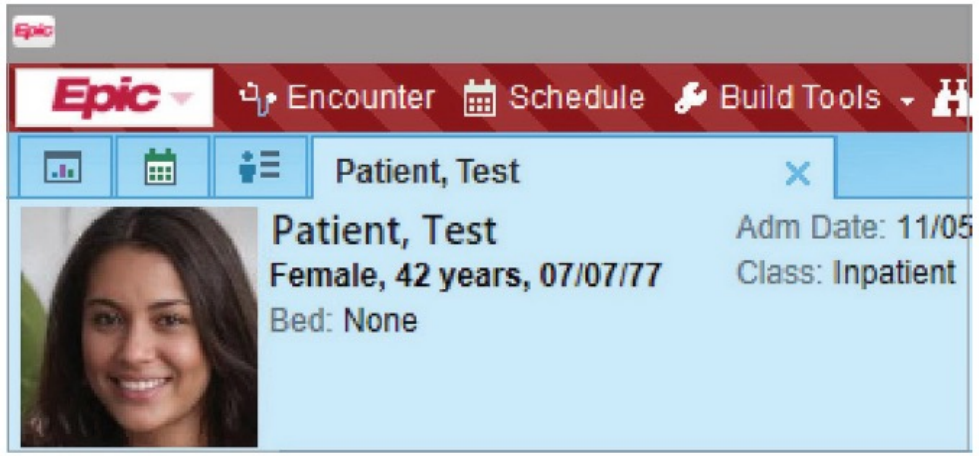
JAMA Network | Open

Original Investigation | Emergency Medicine

Association of Display of Patient Photographs in the Electronic Health Record With Wrong-Patient Order Entry Errors

Hojjat Salmasian, MD, PhD, MPH; Bonnie B. Blanchfield, ScD; Kelley Joyce, BS; Kaila Centeio, BA; Gordon B. Schiff, MD; Adam Wright, PhD; Christopher W. Baugh, MD, MBA; Jeremiah D. Schuur, MD, MHS; David W. Bates, MD; Jason S. Adelman, MD, MS; Adam B. Landman, MD, MS, MIS, MHS

Figure 1. Patient Photograph Feature in the Epic Electronic Health Record



Demographic data are not from a real patient. The image of the face is also not of a real human; it was generated using Style Generative Adversarial Network (owned by Nvidia). The screenshot is used with permission from Epic Systems Corporation.

Salmasian H, Blanchfield BB, Joyce K, Centeio K, Schiff GB, Wright A, Baugh CW, Schuur JD, Bates DW, Adelman JS, Landman AB. Association of Display of Patient Photographs in the Electronic Health Record With Wrong-Patient Order Entry Errors. JAMA Netw Open. 2020 Nov 2;3(11):e2019652. PMID: 33175173

Likelihood of Wrong Patient Order Entry Measured by retract and reorder (RAR)

Table 2. Results of Logistic Regression Model

Variable	Odds ratio (95% CI)
Study group	
Photograph	0.57 (0.52-0.61)
No photograph	1 [Reference]
Patient	
Race	
Hispanic or Latino	0.89 (0.75-1.05)
White	0.92 (0.85-0.99)
Other	0.92 (0.82-1.03)
Black	1 [Reference]
Ethnicity	
Non-Hispanic	1.03 (0.92-1.16)
Other	1.15 (0.94-1.40)
Hispanic	1 [Reference]
Sex	
Male	1.02 (0.96-1.09)
Female	1 [Reference]
Practitioner type	
Resident or fellow	1.05 (0.98-1.13)
NP or PA	1.08 (0.98-1.18)
Other	0.96 (0.46-2.02)
Attending physician	1 [Reference]
ESI score	
1 (Immediate)	0.33 (0.25-0.44)
2 (Emergency)	0.74 (0.69-0.78)
4 (Less urgent)	1.96 (1.72-2.24)
5 (Nonurgent)	1.25 (0.67-2.33)
3 (Urgent)	1 [Reference]
Time of order	
Shift	
Night	0.94 (0.88-1.00)
Day	1 [Reference]
No. of workspaces	
1-4	1.06 (1.03-1.11)
Intercept	1 [Reference]

Abbreviations: ESI, Emergency Severity Index; NP, nurse practitioner; PA, physician assistant.

Salmasian H, Blanchfield BB, Joyce K, Centeio K, Schiff GB, Wright A, Baugh CW, Schuur JD, Bates DW, Adelman JS, Landman AB. Association of Display of Patient Photographs in the Electronic Health Record With Wrong-Patient Order Entry Errors. JAMA Netw Open. 2020 Nov 2;3(11):e2019652. PMID: 33175173

Transition Comedy Slide

- COVID Stuff
- New Stuff

(Yes that's Bill in full virtual care COVID regalia)

EnM
ENDOCRINOLOGY AND METABOLISM

Review Article

Endocrinol Metab 2021 Forthcoming.
https://doi.org/10.3803/EnM.2021.201
pISSN 2093-596X · eISSN 2093-5978

Continuous Glucose Monitoring in the Hospital

M. Citlalli Perez-Guzman[1], Trisha Shang[2], Jennifer Y. Zhang[2], Donna Jornsay[3], David C. Klonoff[4]

[1]Division of Endocrinology, Metabolism, and Lipids, Department of Medicine, Emory University, Atlanta, GA, USA; [2]Diabetes Technology Society, Burlingame, CA, USA; [3]Diabetes Program, Mills-Peninsula Medical Center, Burlingame, CA, USA; [4]Diabetes Research Institute, Mills-Peninsula Medical Center, San Mateo, CA, USA

Reducing Inpatient Hypoglycemia in the General Wards Using Real-time Continuous Glucose Monitoring: The Glucose Telemetry System, a Randomized Clinical Trial

Lakshmi G. Singh[1], Medha Satyarengga[2], Isabel Marcano[3], William H. Scott[1], Lillian F. Pinault[1], Zhaoyong Feng[4], John D. Sorkin[5], Guillermo E. Umpierrez[6] **and** Elias K. Spanakis[1,3]

- Summary of CGM in the acute care setting (~20 years)
- Spurred by COVID demands (nursing staffing / PPE / exposure) and recent advances in CGM in the commercial sector

Implementation of Continuous Glucose Monitoring in the Hospital: Emergent Considerations for Remote Glucose Monitoring During the COVID-19 Pandemic

Rodolfo J. Galindo, MD, Grazia Aleppo, MD, David C. Klonoff, MD, more... Show all authors

First Published June 14, 2020 | Article Commentary | Find in PubMed | Check for updates
https://doi.org/10.1177/1932296820932903

Diabetes Care

Remote Continuous Glucose Monitoring With a Computerized Insulin Infusion Protocol for Critically Ill Patients in a COVID-19 Medical ICU: Proof of Concept

Georgia M. Davis,[1] Eileen Faulds,[2] Tara Walker,[3] Debbie Vigliotti,[4] Marina Rabinovich,[4] Joi Hester,[5] Limin Peng,[6] Barbara McLean,[7] Patricia Hannon,[7] Norma Poindexter,[7] Petrena Saunders,[7] Citlalli Perez-Guzman,[1] Seema S. Tekwani,[8] Greg S. Martin,[8] Guillermo Umpierrez,[1] Shivani Agarwal,[9] Kathleen Dungan,[2] and Francisco J. Pasquel[1]

https://doi.org/10.2337/dc20-2085

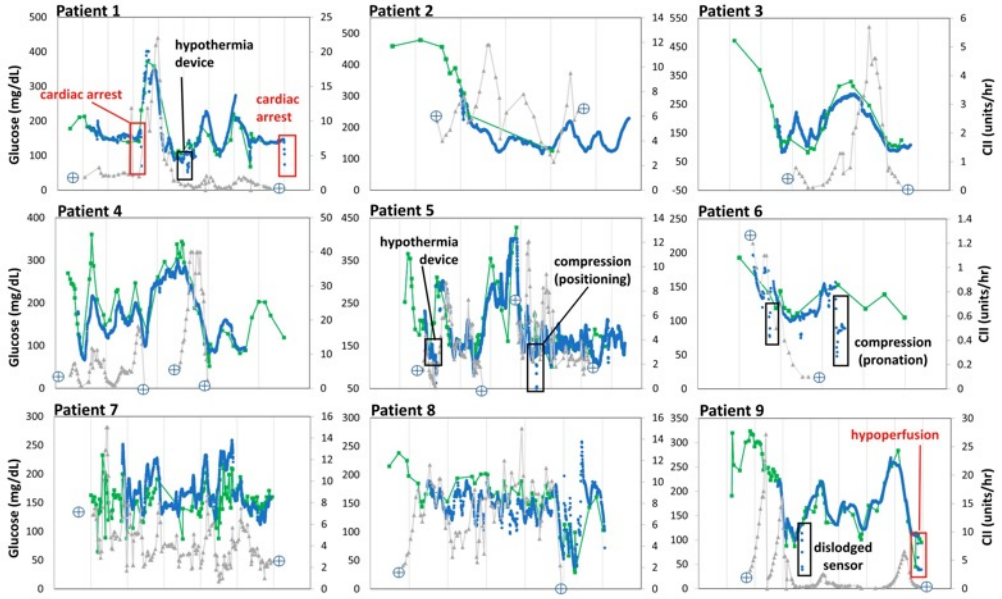
CGM in the Hospital Setting

- Highly effective at preventing lows and have potential to prevent frequent POC needlesticks

  "Hypoglycemic events were identified more frequently with RT-CGM than POC testing"

- Yet another potential source of excessive data (288 data points in 24 hours)
- Some concerns regarding latency and calibration
- Considerations
  - Vitamin C
  - Compression of device
  - Signal Loss
  - Hypothermia Protocols
  - MRI

It's only going to get better



Rapid response to COVID-19: health informatics support for outbreak management in an academic health system.
Reeves JJ, et al. JAMIA. 2020

- Examples of early outbreak management dashboard (left)
- Telemedicine video-interface (right)

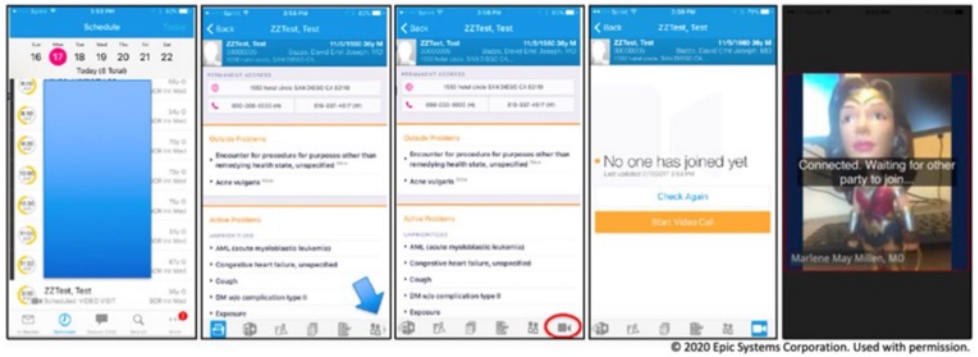


Figure 3. Telemedicine - Video Visit. Graphic displaying the layout of UC San Diego's virtual visit encounter.

doi: 10.1093/jamia/ocaa037

Rapid response to COVID-19: health informatics support for outbreak management in an academic health system.

Reeves JJ, et al. JAMIA. 2020

JAMIA
A SCHOLARLY JOURNAL OF INFORMATICS IN HEALTH AND BIOMEDICINE

- **Discussion:** The EHR became an essential tool for rapid deployment of standardized processes.
- The team at UC San Diego Health built multiple COVID-19-specific tools to support outbreak management, including scripted triaging, electronic check-in, standard ordering and documentation, secure messaging, real-time data analytics, and telemedicine capabilities.
- Challenges included the need to frequently adjust build to meet rapidly evolving requirements, communication, and adoption, and to coordinate the needs of multiple stakeholders while maintaining high-quality, pre-pandemic medical care.
- **Conclusion: One of the earliest examples of leveraging the EHR and its capabilities to respond to the COVID-19 crisis at an academic health center**

doi: 10.1093/jamia/ocaa037

SARS-CoV-2 Infection after Vaccination in Health Care Workers in California

- Pooled data from Epic UCSD and UCLA both testing and vaccination status
- Vaccinated health workers were systematically tested via PCR
- Low positive rate post vaccination 1% helped to corroborate the trial data using real world data

The NEW ENGLAND JOURNAL of MEDICINE

Table 1. New SARS-CoV-2 Infections among Vaccinated Health Care Workers from December 16, 2020, through February 9, 2021.

Days after Vaccination	Vaccinated Persons		
	With New Infection (N=379)	Tested (N=14,604)*	Eligible for Testing (N=36,659)†
	number		*number (percent)*
Dose 1			
Days 1–7	145	5794	35,673 (97.3)
Days 8–14	125	7844	34,404 (93.8)
Days 15–21	57	7958	32,667 (89.1)
Day 22 or later, before dose 2	15	4286	32,327 (88.2)
Dose 2			
Days 1–7	22	5546	23,100 (63.0)
Days 8–14	8	4909	16,082 (43.9)
Day 15 or later	7	4167	14,990 (40.9)

Rapid Implementation of a Vaccination Superstation

Christopher A. Longhurst, MD, MS[1,2]; Brendan Kremer, MHA[1]; Patricia S. Maysent, MBA, MHA[1]

Transitions from One Electronic Health Record to Another: Challenges, Pitfalls, and Recommendations

Chunya Huang, Ross Koppel, John D. McGreevey III, Catherine K. Craven, Richard Schreiber

Exhaustive literature review related to EHR to EHR transitions

PubMed hit for ~2500 potentials but really only ~20 relevant full papers included

So this is a topic that needs more research and guidance (especially in this era of consolidations)

10 Domains for successful transitions

Challenges

- Financial
- Personnel
- Limited legacy access post conversion = safety
- Data integrity
- Cybersecurity
- Semantic Interoperability

The End

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