

Update in Clinical Informatics

(Not Batman and Robin, but thing 1 and thing 2)

AMDIS PCC
Ojai, California
June 2023

Colin Banas, CMO, *Dr. First*

Bill Galanter, Assoc Prof, University of Illinois Chicago



UNIVERSITY OF ILLINOIS
Hospital & Health Sciences System
Changing medicine. For good.

Conflicts



Dr. "Daddy Warbuck's" Banas
-DrFirst



zilch

Review Methodology



*What struck him as cool last year
(June 2022 – June 2023).*



Clinical studies in last year.

Bills methodology to find articles

Select CI MESH headings from major MESH headers of "clinical", "medical", "nursing", "dental", "health". Did not include straight technology(i.e. "Biomedical Engineering", "Biomedical technology", "Electronics, Medical" etc..)

This gives the following concepts;

Adverse Drug Reaction Reporting Systems, Ambulatory Care Information Systems, Artificial Intelligence, Biological Ontologies, clinical informatics , Clinical Laboratory Information Systems, Clinical Pharmacy Information Systems, Community Networks, Consumer Health Informatics, Decision Making, Computer-Assisted, Decision Support Systems, Clinical, Decision Support Techniques, Dental Informatics, Diagnosis, Computer-Assisted, Drug Therapy, Computer-Assisted, Electronic Prescribing, Geographic Information Systems, Health Information Exchange, Health Information Systems, Health Smart Cards, Hospital Information Systems, Image Interpretation, Computer-Assisted, Information Systems, Integrated Advanced Information Management Systems, Knowledge Bases, Medical Informatics Applications, Medical Informatics Computing, Medical Order Entry Systems, Medical Record Linkage, Medical Records Systems, Computerized, Nursing Informatics, Operating Room Information Systems, Patient Generated Health Data, Patient Portals, Point-of-Care Systems, Prescription Drug Monitoring Programs, Public Health Informatics, Radiology Information Systems, Radiotherapy, Computer-Assisted, Reminder Systems, Telemedicine

This is simplified by using proximal concepts that contain many of the sub-concepts of interest;

"Artificial Intelligence"[MESH] OR "Clinical Laboratory Information Systems"[MESH] OR "Consumer Health Informatics"[MESH] OR "Therapy, Computer-Assisted "[MESH] OR "Decision Support Techniques"[MESH] OR "Dental Informatics"[MESH] OR "Drug Information Services"[MESH] OR "Electronic Prescribing"[MESH] OR "Health Records, Personal"[MESH] OR "Hospital Information Systems"[MESH] OR "Information Systems"[MESH] OR "Medical Informatics"[MESH] OR "Medical Record Linkage"[MESH] OR "Medical Records Systems, Computerized"[MESH] OR "Nursing Informatics"[MESH] OR "Public Health Informatics"[MESH] OR "Radiology Information Systems"[MESH] OR "Reminder Systems"[MESH] OR "Telemedicine"[MESH]

Bill's methodology (cont.)

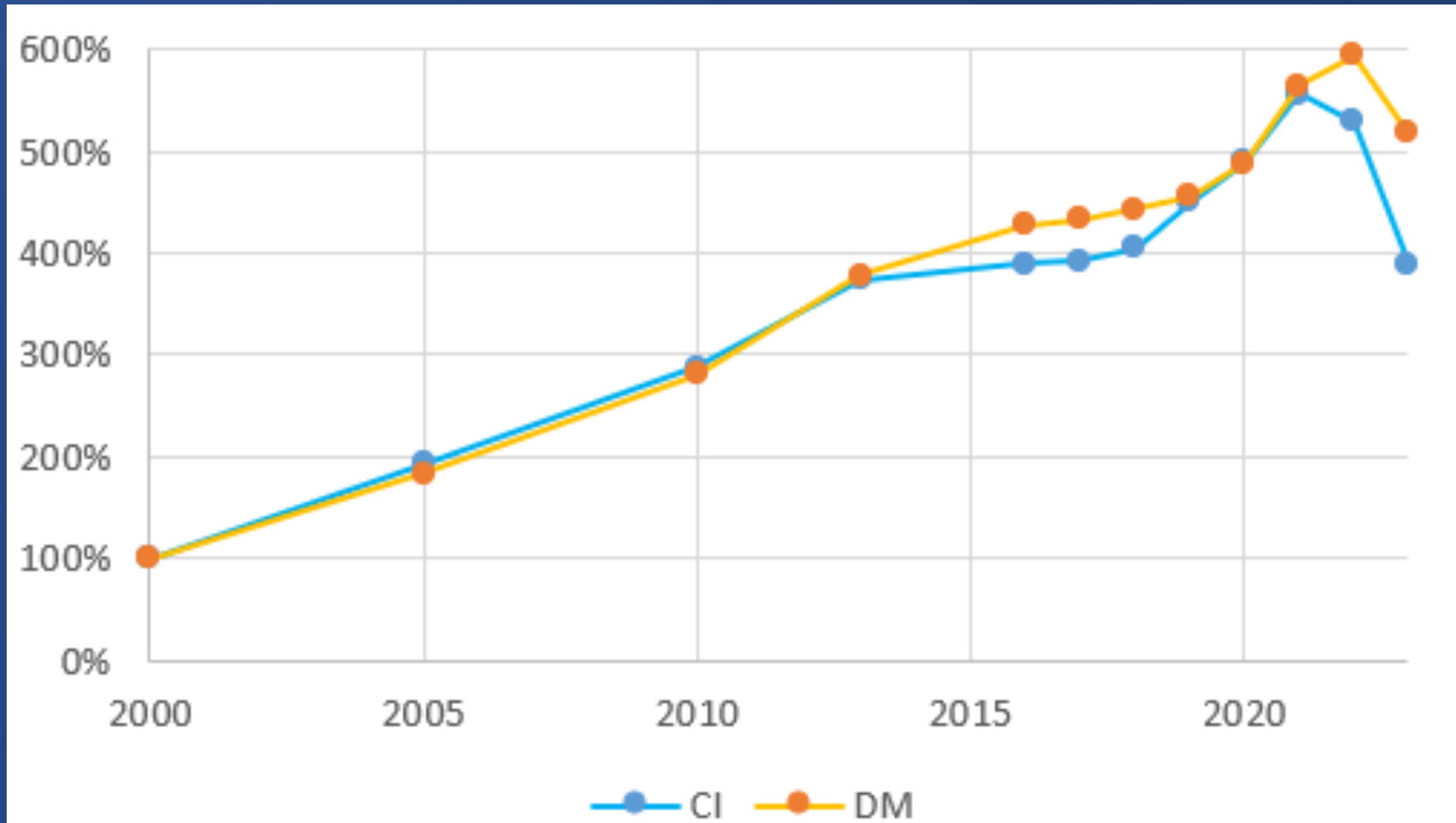
From 6/1/22→5/31/23 this query gave 38,119 entries

For the rest of the analysis, only titles with English (99%) abstracts were included: 35,201

From this 35,201 entries, the trials, 784, were reviewed and a sample selected for presentation

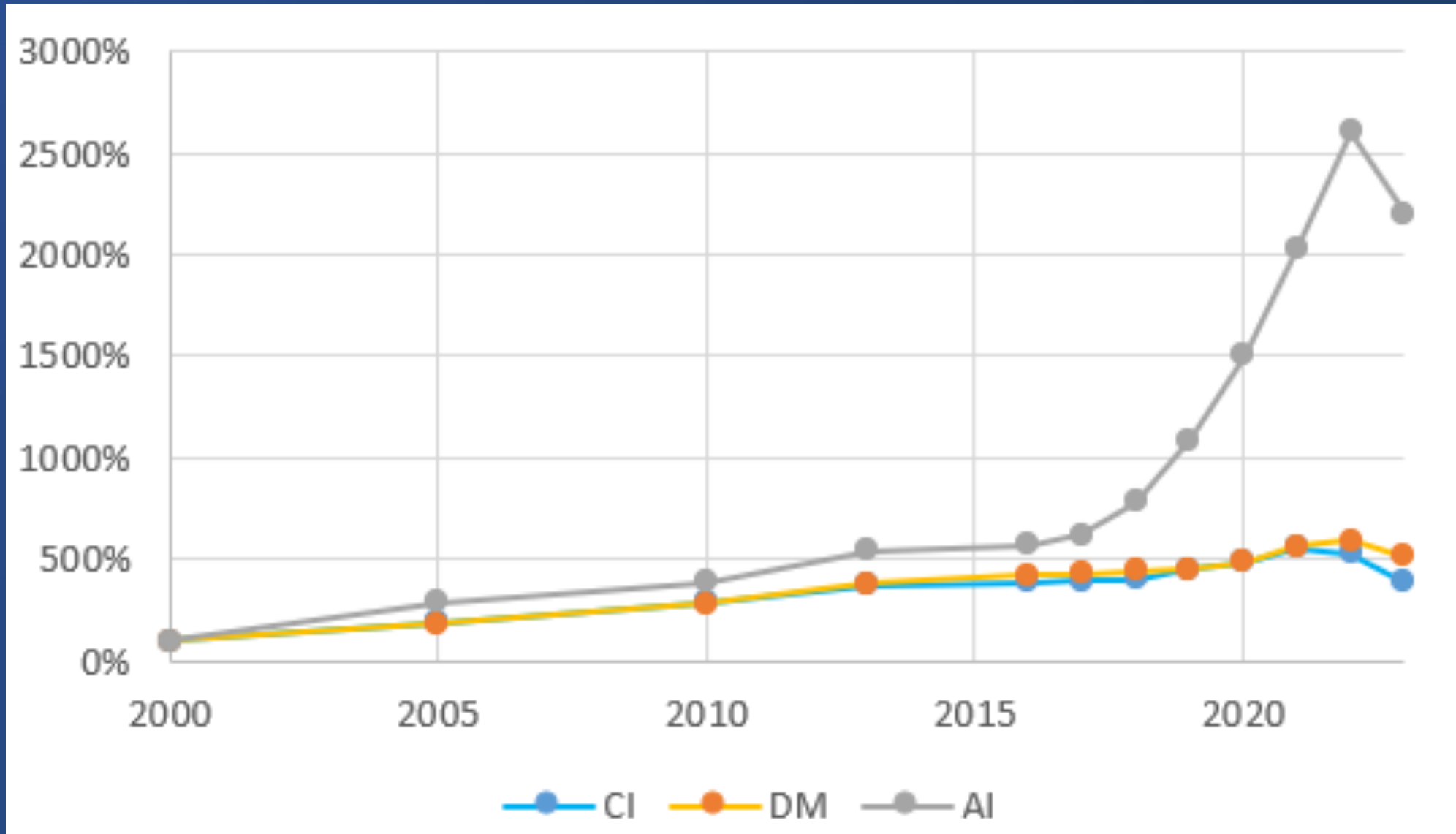
Growth in Publications

(compared to 2000, using Diabetes Type 2 (DM) as comparator)



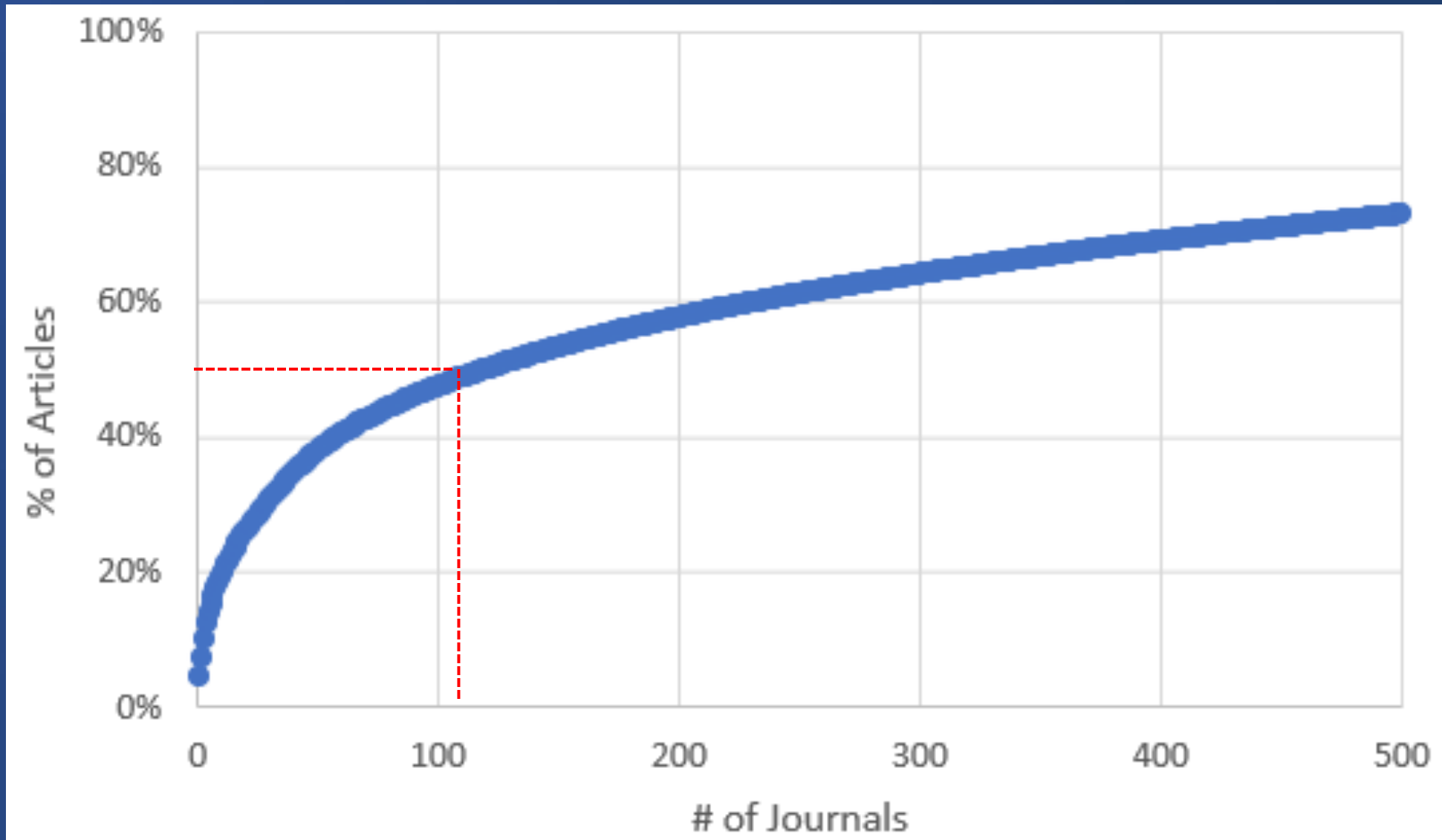
Growth in Publications

(compared to 2000, using Diabetes Type 2 (DM) and "Artificial Intelligence" [MESH] comparator)



What Journals?

Proportion of Articles vs. # of Journals



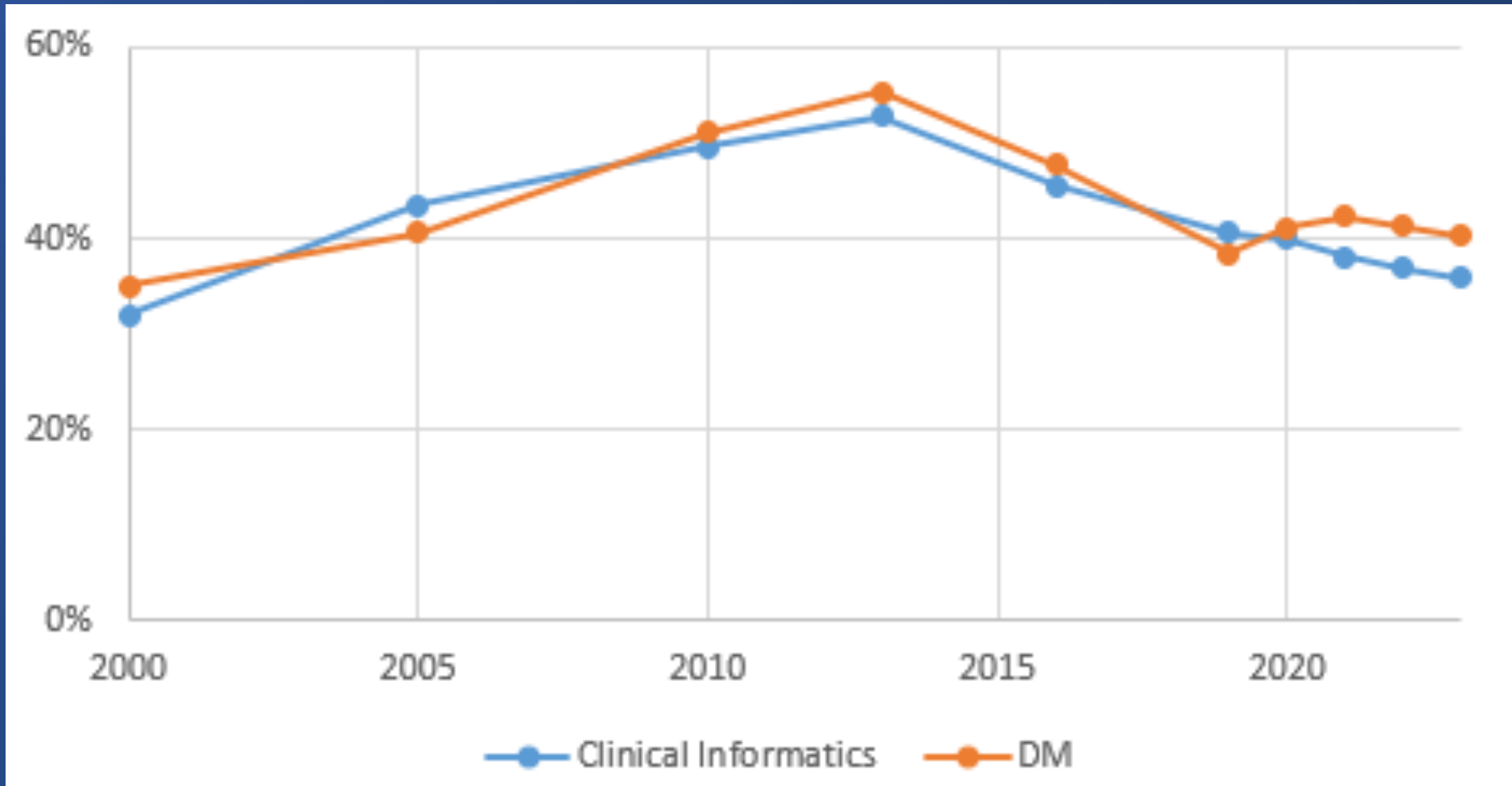
What Journals?

Adv Sci (Weinh)	IEEE Trans Cybern	Med Image Anal
Ann Surg Oncol	IEEE Trans Med Imaging	Med Phys
Annu Int Conf IEEE Eng Med Biol Soc	IEEE Trans Neural Netw Learn Syst	Medicine (Baltimore)
Appl Clin Inform	IEEE Trans Pattern Anal Mach Intell	Methods
Artif Intell Med	IEEE/ACM Trans Comput Biol Bioinform	Nat Commun
Bioinformatics	Int J Comput Assist Radiol Surg	Nature
Biomed Res Int	Int J Environ Res Public Health	Neural Netw
BMC Bioinformatics	Int J Med Inform	Nucleic Acids Res
BMC Health Serv Res	Int J Med Robot	Phys Med
BMC Med Inform Decis Mak	Int J Mol Sci	Phys Med Biol
BMJ Open	J Am Med Inform Assoc	PLoS Comput Biol
Brief Bioinform	J Appl Clin Med Phys	PLoS One
Chemosphere	J Biomed Inform	Proc Natl Acad Sci U S A
Comput Biol Med	J Chem Inf Model	Radiology
Comput Intell Neurosci	J Digit Imaging	Radiother Oncol
Comput Math Methods Med	J Environ Manage	Sci Data
Comput Methods Programs Biomed	J Environ Public Health	Sci Rep
Environ Sci Pollut Res Int	J Med Internet Res	Sci Total Environ
Eur Radiol	J Robot Surg	Sensors (Basel)
Front Endocrinol (Lausanne)	JAMA Netw Open	Spectrochim Acta A Mol Biomol Spectro
Front Immunol	Magn Reson Med	Stud Health Technol Inf
Front Public Health	Math Biosci Eng	Surg Endosc
IEEE J Biomed Health Inform	Med Biol Eng Comput	Telemed J E Health

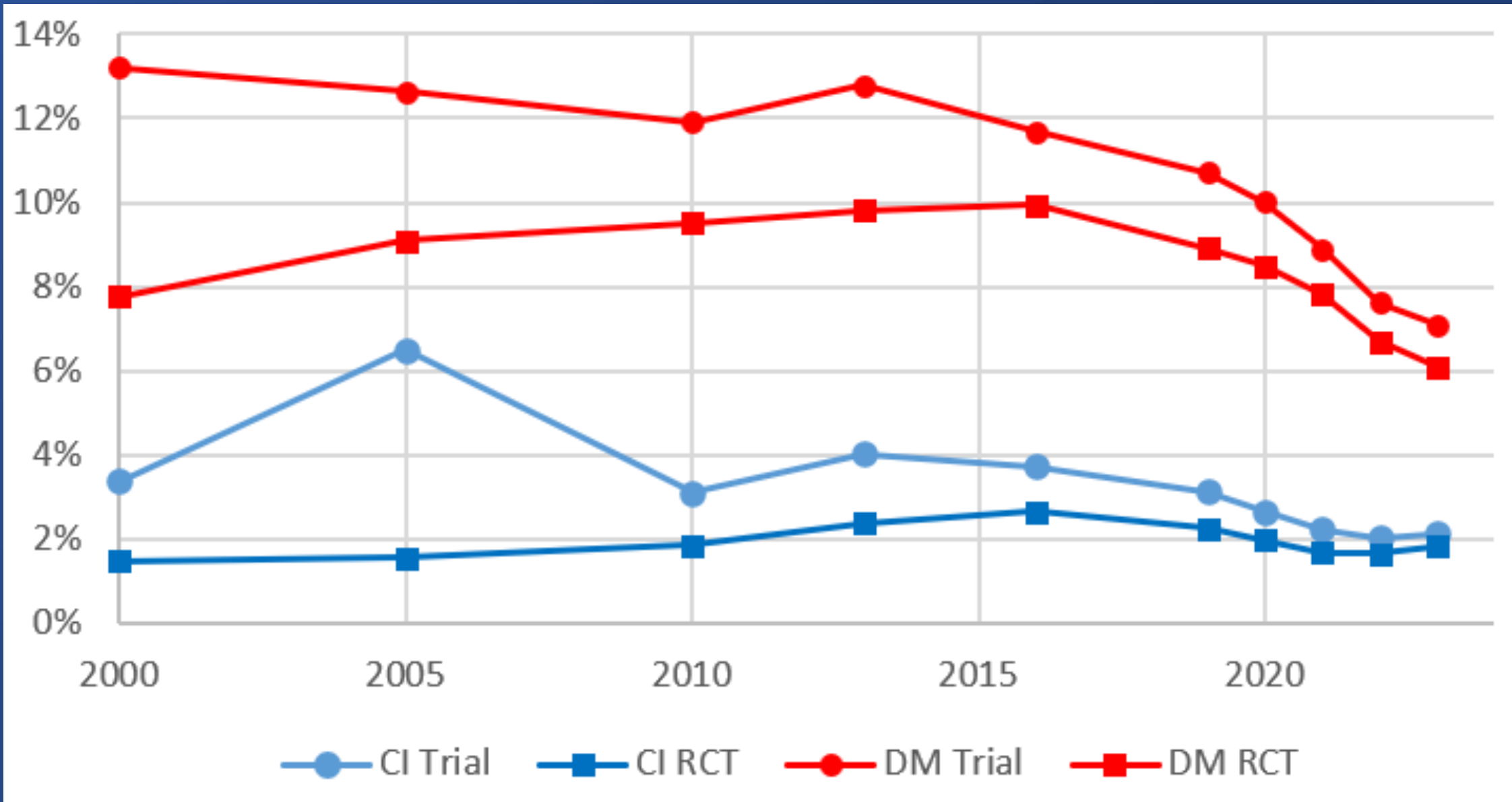
What Journals are the trials published in ?

AJR Am J Roentgenol	Eur Arch Otorhinolaryngol	JAMA Netw Open
Am Heart J	Eur J Radiol	JMIR Mhealth Uhealth
Ann Intern Med	Eur Radiol	Lancet
Ann Surg Oncol	Eur Urol	Lancet Digit Health
Appl Clin Inform	Eur Urol Focus	Med Decis Making
BJU Int	Eur Urol Oncol	Medicine (Baltimore)
BMC Anesthesiol	Front Public Health	Nutrients
BMC Cancer	Gastrointest Endosc	Parkinsonism Relat Disord
BMC Health Serv Res	Int J Cardiol	PeerJ
BMC Med Inform Decis Mak	Int J Environ Res Public Health	PLoS One
BMC Nephrol	Int J Radiat Oncol Biol Phys	Radiat Oncol
BMC Public Health	Int Orthop	Radiology
BMJ	J Am Med Inform Assoc	Radiother Oncol
BMJ Open	J Cancer Res Ther	Sci Rep
Cancer Med	J Consult Clin Psychol	Sensors (Basel)
Circ Cardiovasc Qual Outcomes	J Diabetes Sci Technol	Spine (Phila Pa 1976)
Clin Infect Dis	J Endourol	Stroke
Clin Oncol (R Coll Radiol)	J Gen Intern Med	Support Care Cancer
Clin Radiol	J Med Internet Res	Surg Endosc
Comput Math Methods Med	J Med Syst	Telemed J E Health
Contemp Clin Trials	J Robot Surg	Trials
Contrast Media Mol Imaging	J Telemed Telecare	Ultrasound Med Biol
Endoscopy	JAMA	World J Urol

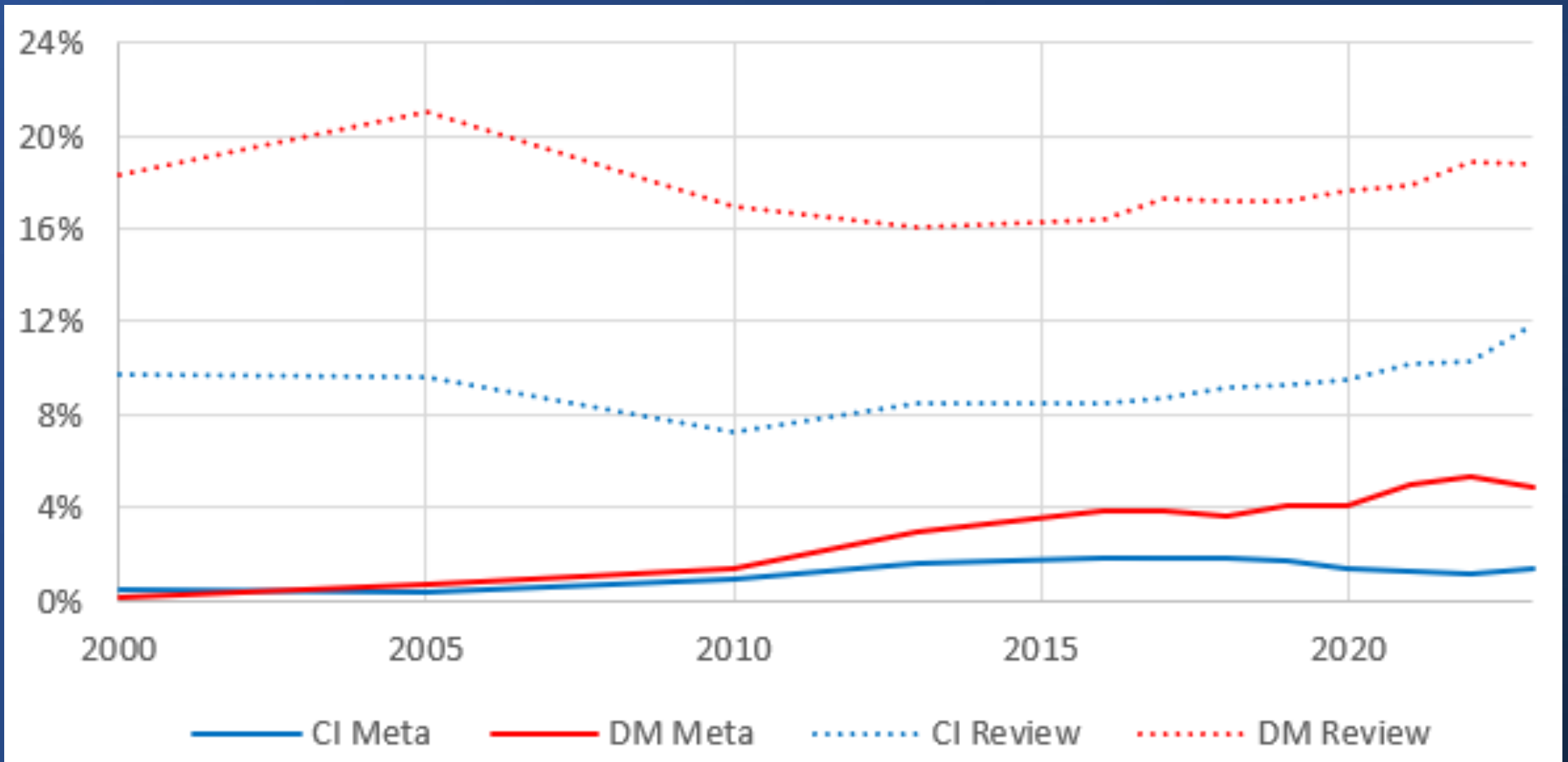
% of publications with any funding



Proportion of publications that are trials or RCTs



Proportion of Publications that are Reviews or Meta-Analyses



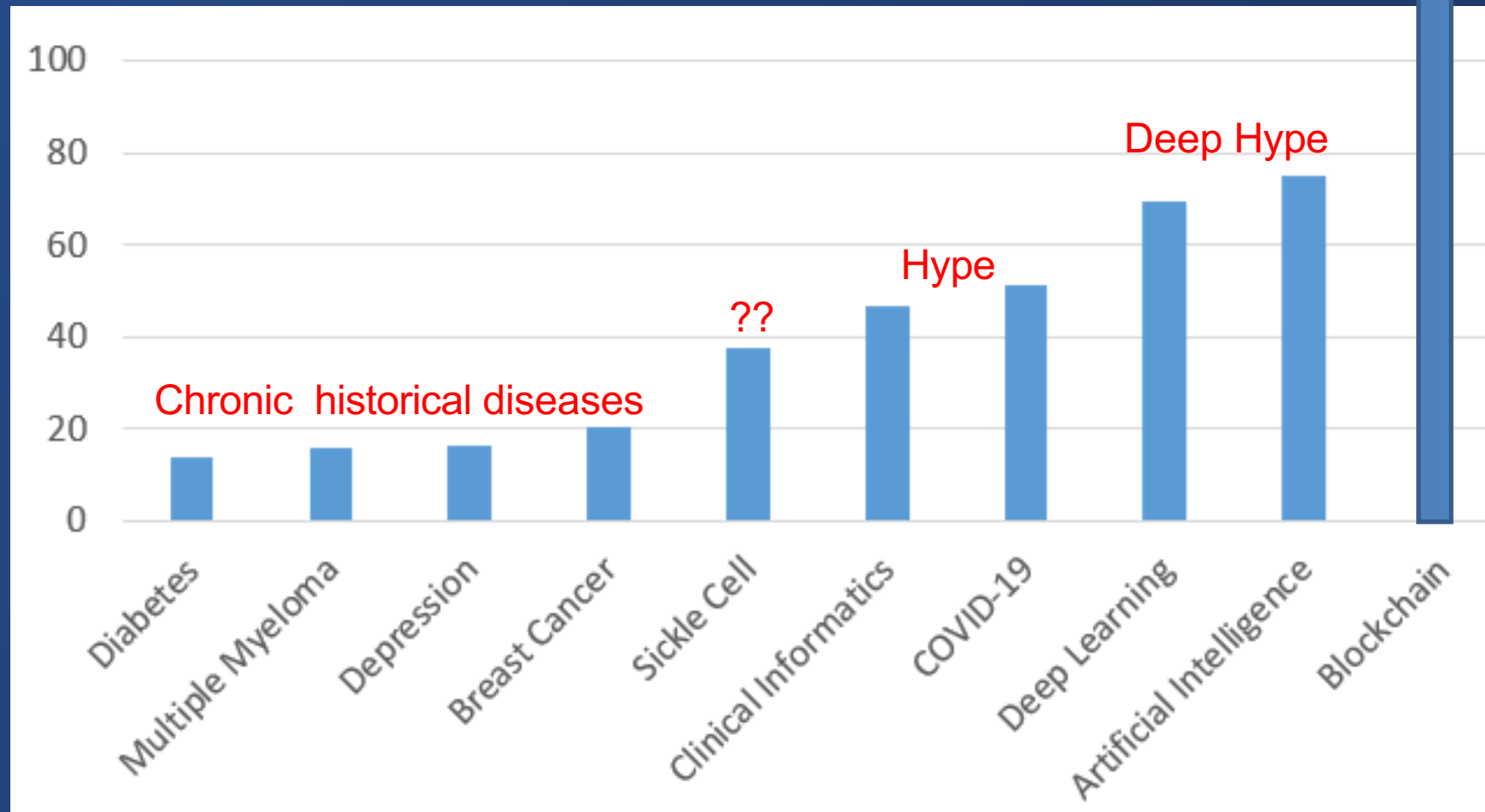
BS/Study Ratio[®]

BS: Opinions, thoughts, anecdotes, cases, whatever, etc.

Study: experiments, cohorts, retro analysis, observations, some type of study.

Infinite Hype
(no trials)

BS/Study Ratio[®]



Text Review Methodology

Cohort

35,201 Medline Publications
-include abstract and title
- 120×10^6 characters
- 16×10^6 "words"

The # of phrases is very, very, large and non manageable (for me and Colin at least...)

Phrases and words were counted in R with help from ChatGPT4, who was unable to come to the meeting this year.

Who is mentioned in the “Corpus”

nurse

pharmacist

therapist

physician

children

practitioner

provider

clinician

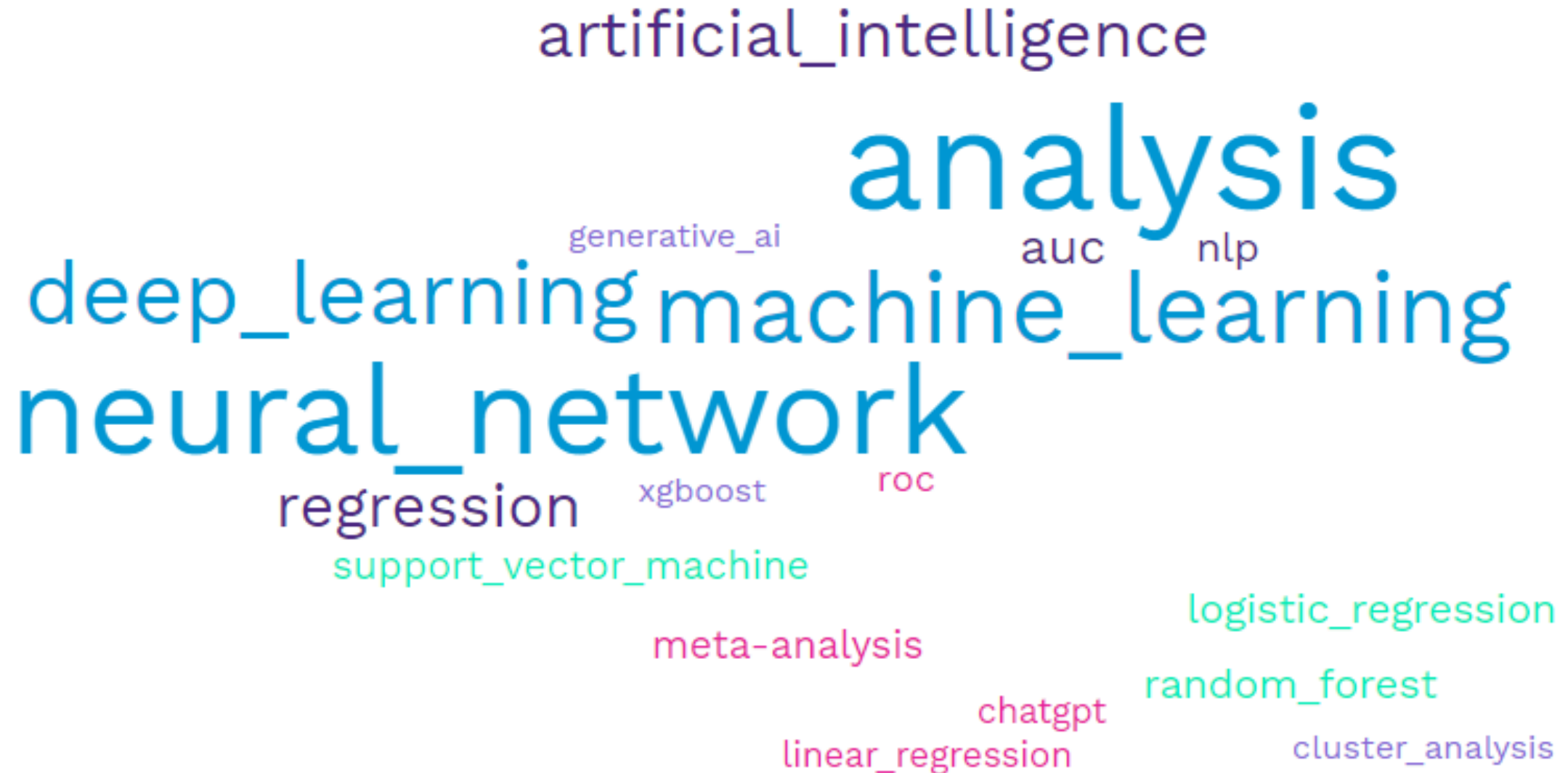
dentist

assistant

counselor

patient

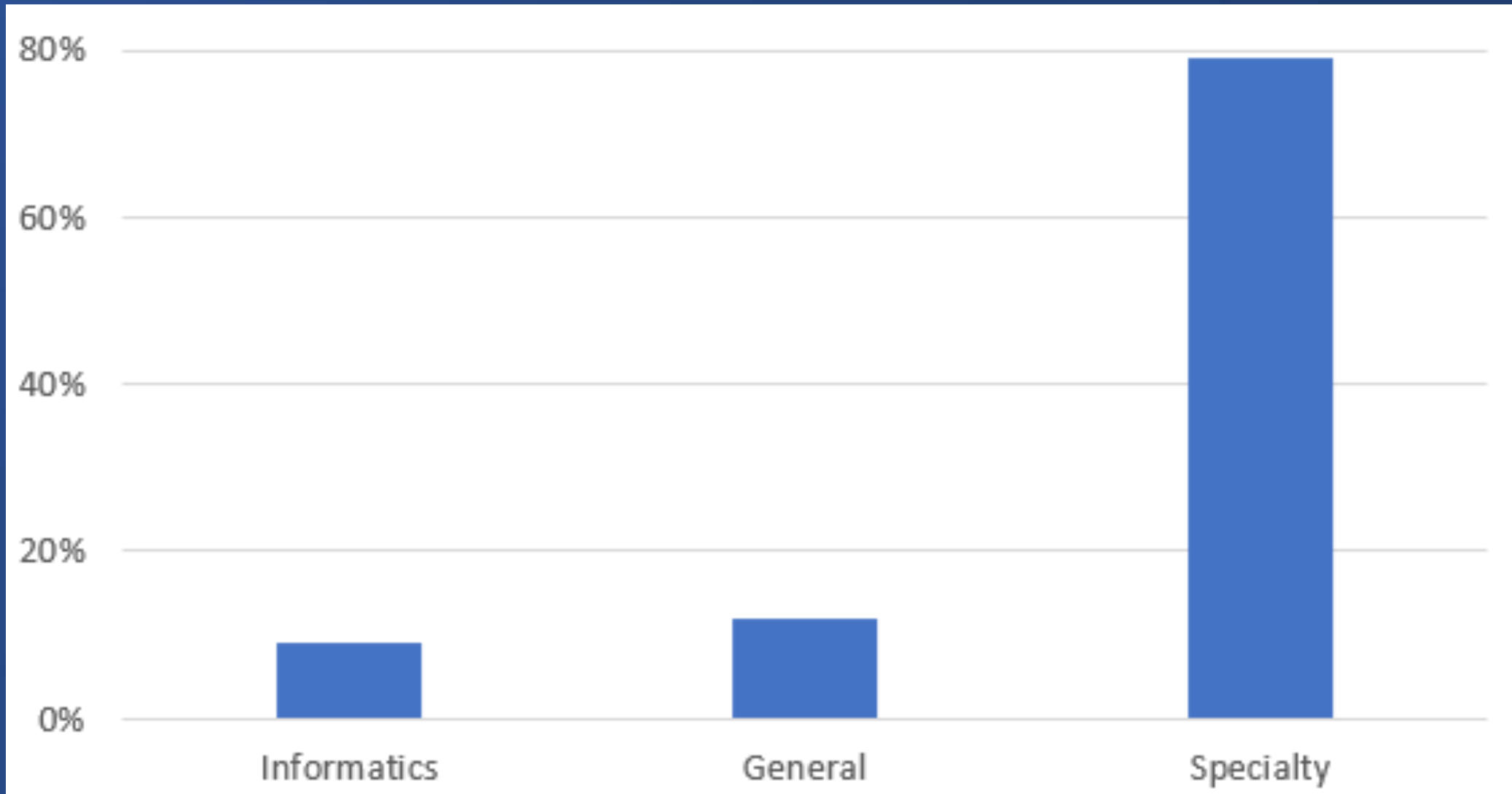
What *analytic concepts* are in the Corpus?



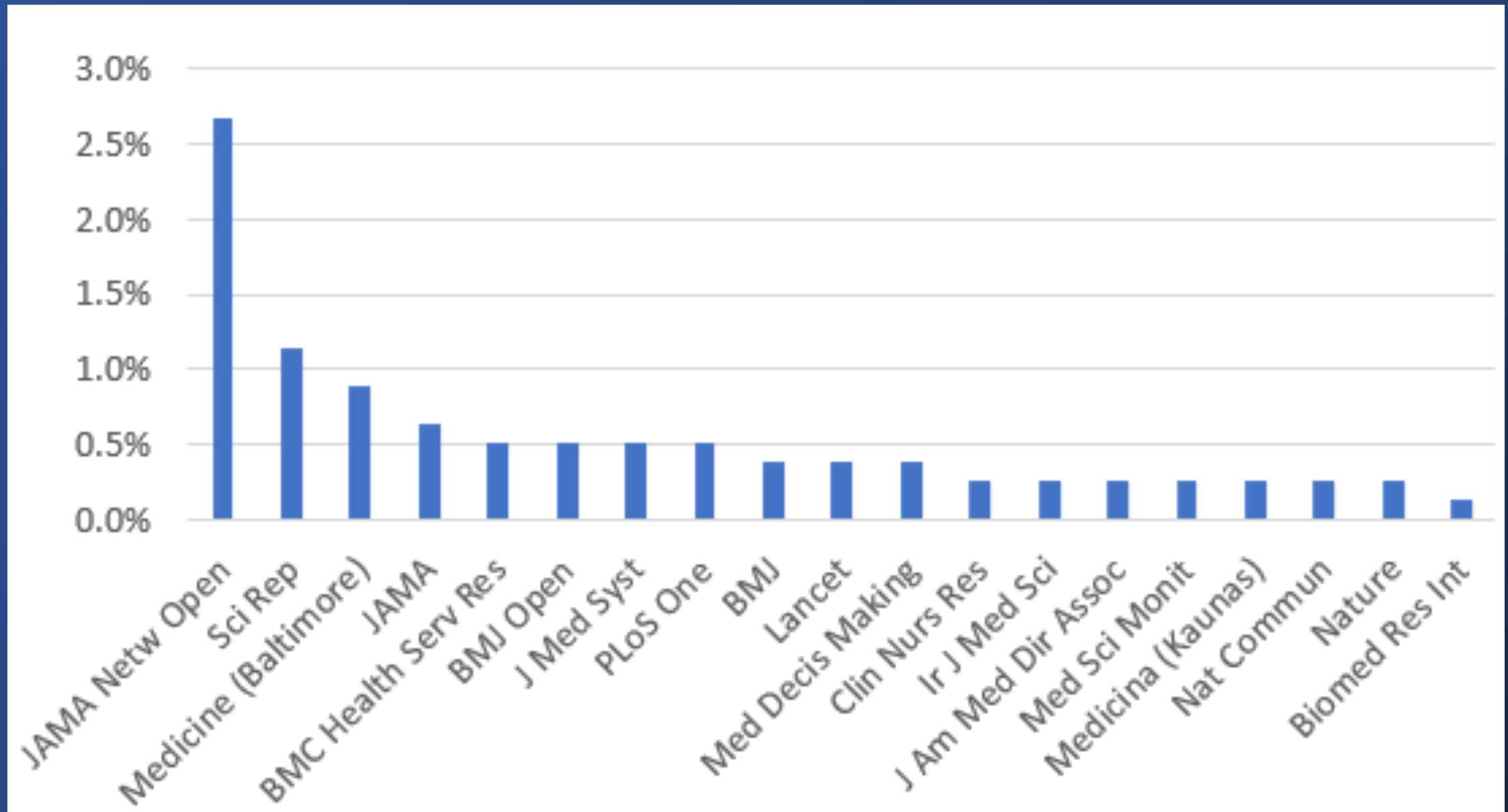
A word cloud of analytic concepts. The words are arranged in a roughly circular pattern, with 'analysis' being the largest and most central. Other prominent words include 'neural_network', 'machine_learning', 'deep_learning', and 'artificial_intelligence'. Smaller words include 'regression', 'support_vector_machine', 'meta-analysis', 'linear_regression', 'chatgpt', 'random_forest', 'cluster_analysis', 'logistic_regression', 'roc', 'auc', 'nlp', 'generative_ai', 'xgboost', and 'meta-analysis'.

artificial_intelligence
analysis
generative_ai
auc
nlp
deep_learning
machine_learning
neural_network
regression
xgboost
roc
support_vector_machine
meta-analysis
logistic_regression
random_forest
cluster_analysis
linear_regression
chatgpt

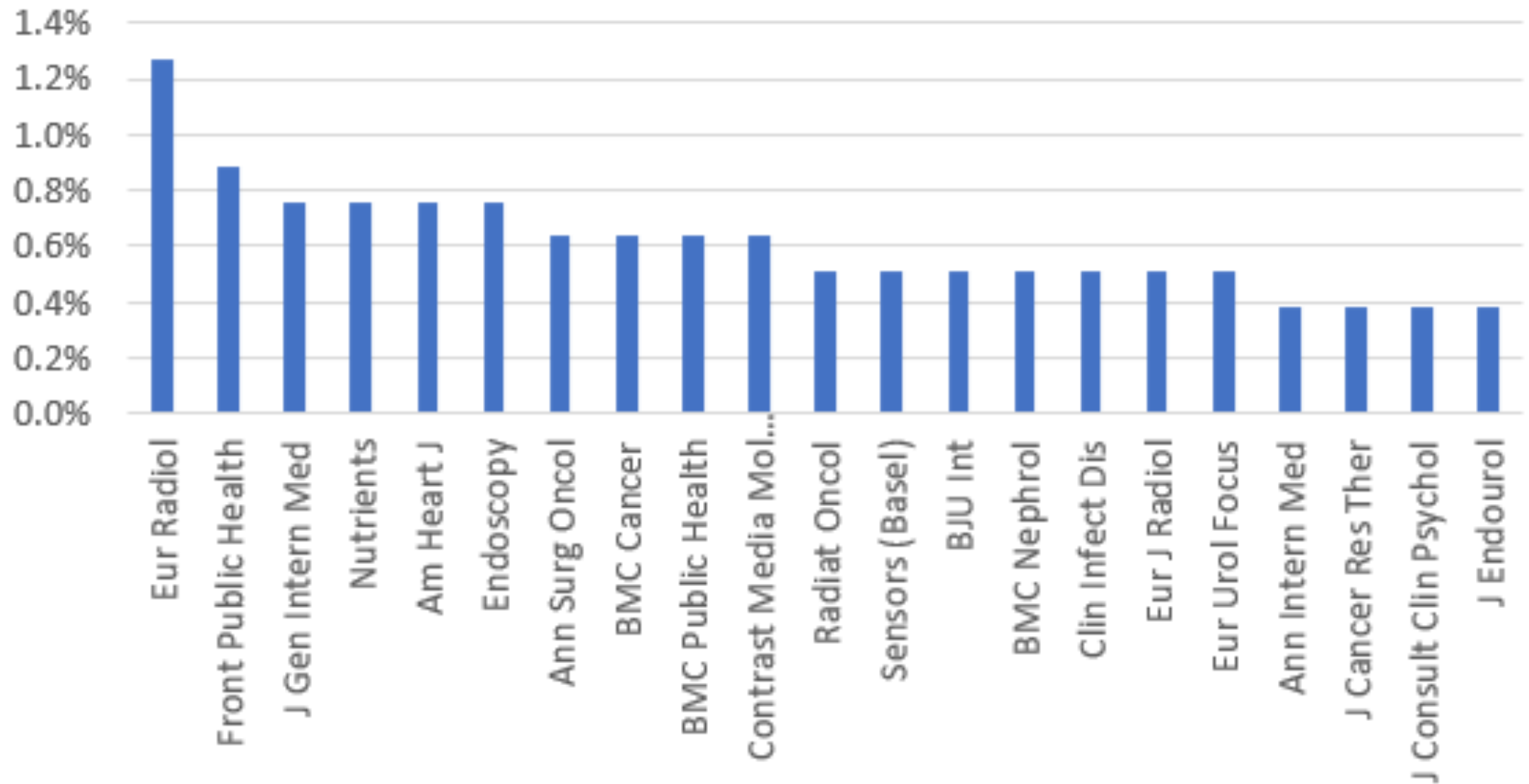
Distribution of articles by type of journal in the *trials* cohort



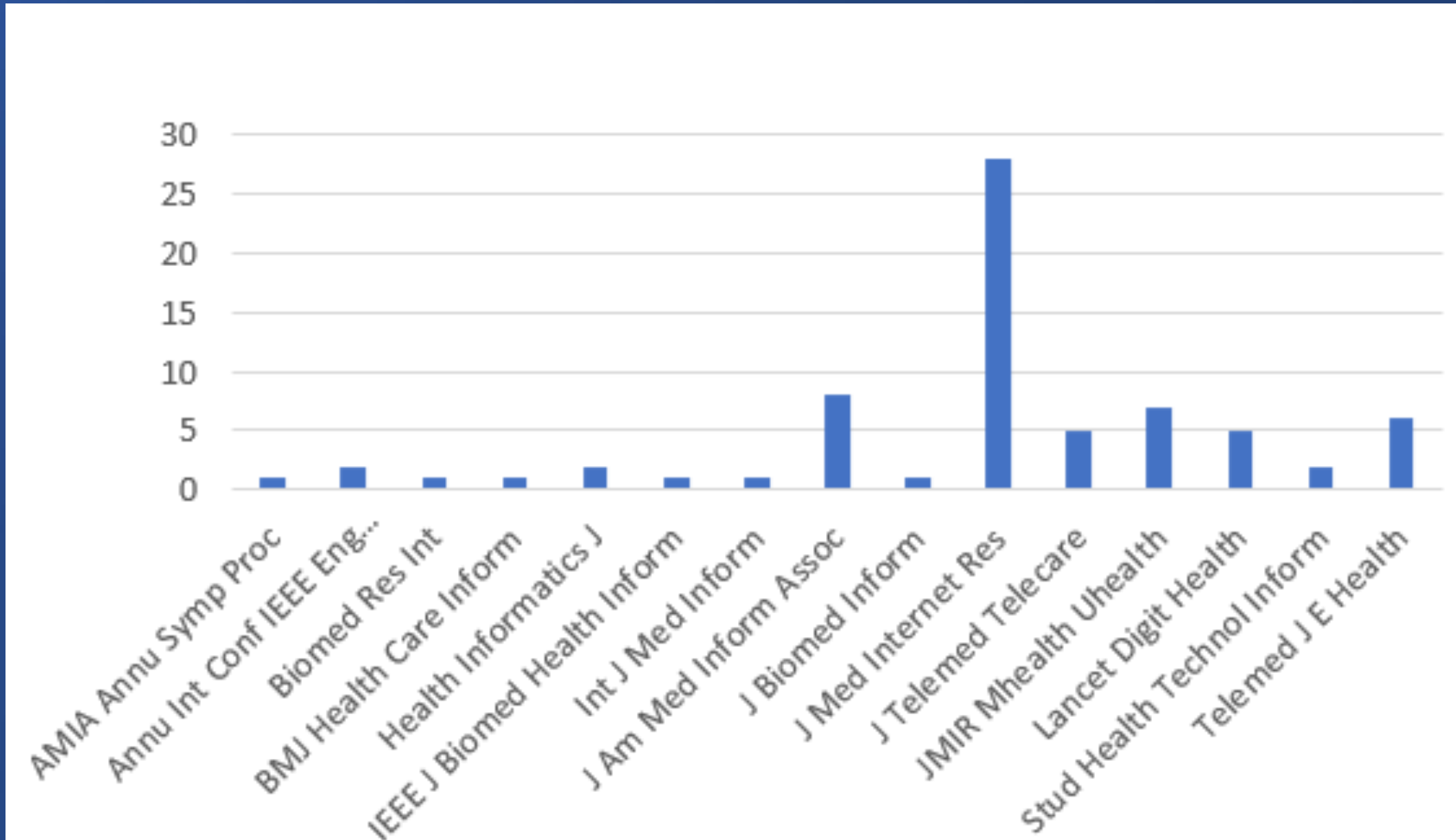
Distribution of “general” journals in the trials cohort



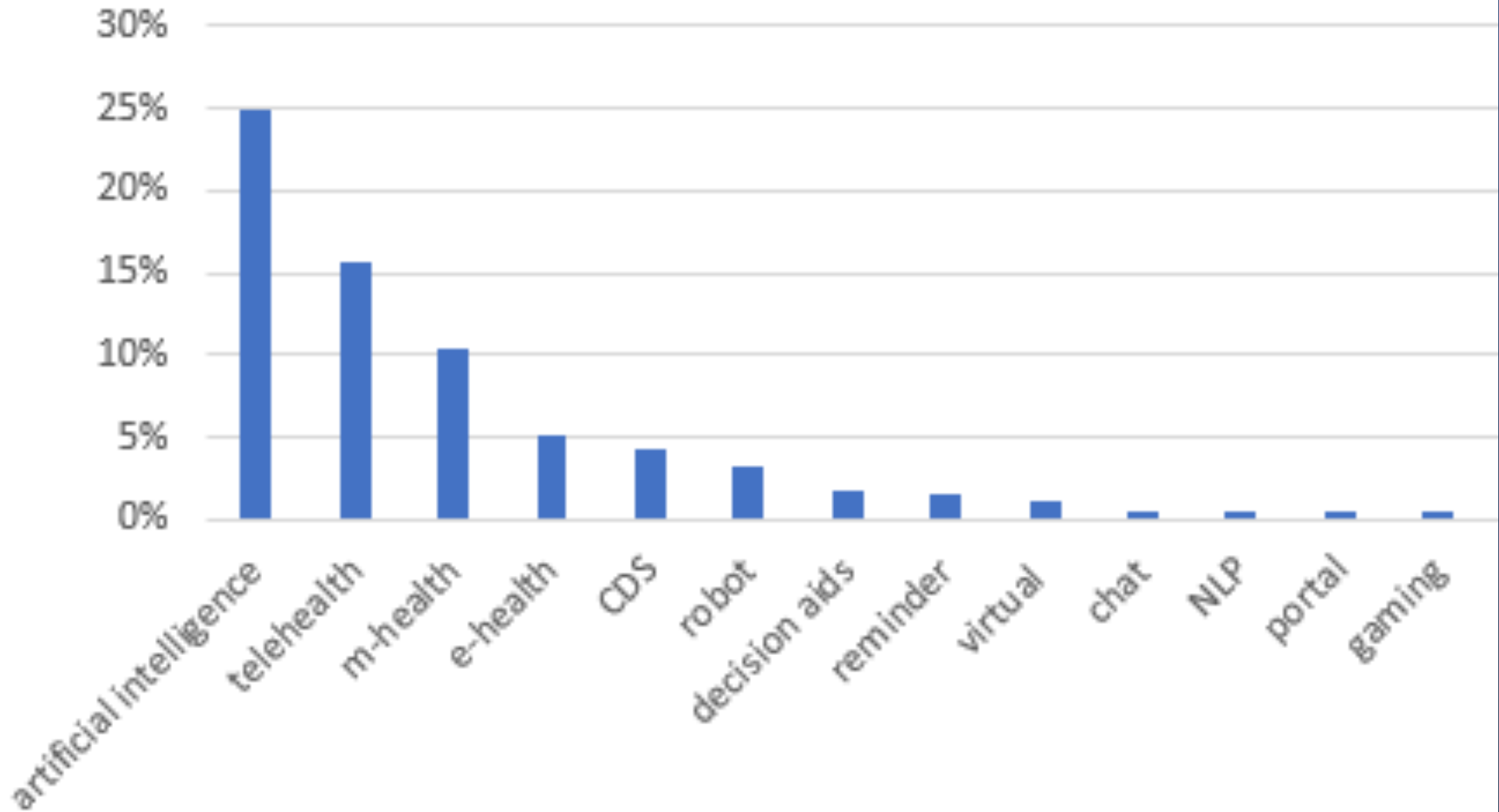
Distribution of “specialty” journals in the *trials* cohort



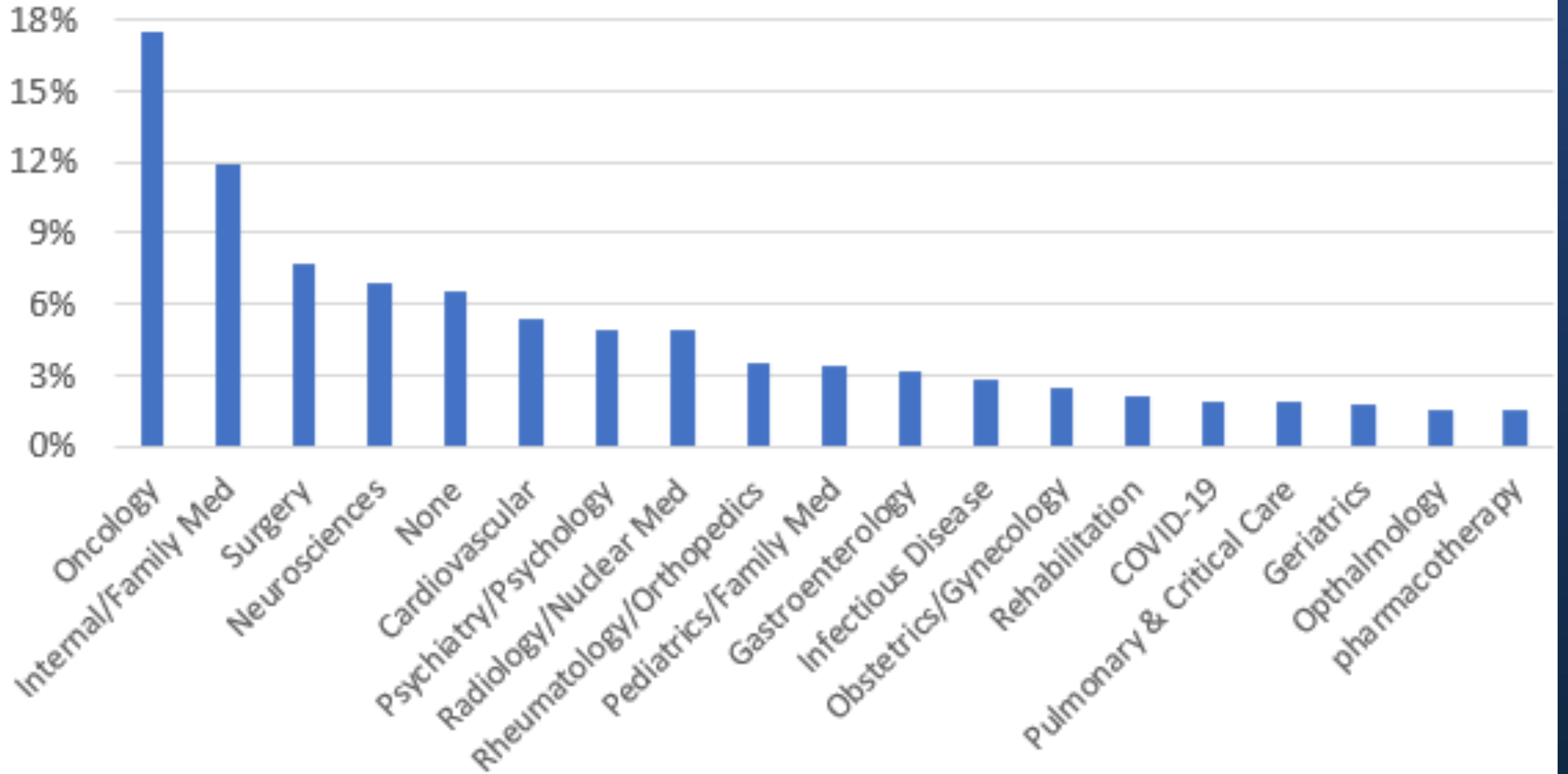
Distribution of “informatics” Journals in the *trials* cohort



Informatics “methods” in the trials



Clinical Areas in the trials





*Transition to Colin –
random cool papers, this time
related to note writing*

CANVA

Coollest
male
doctor
alive in
shorts and
flip flops





Prevalence and Sources of Duplicate Information in the Electronic Medical Record

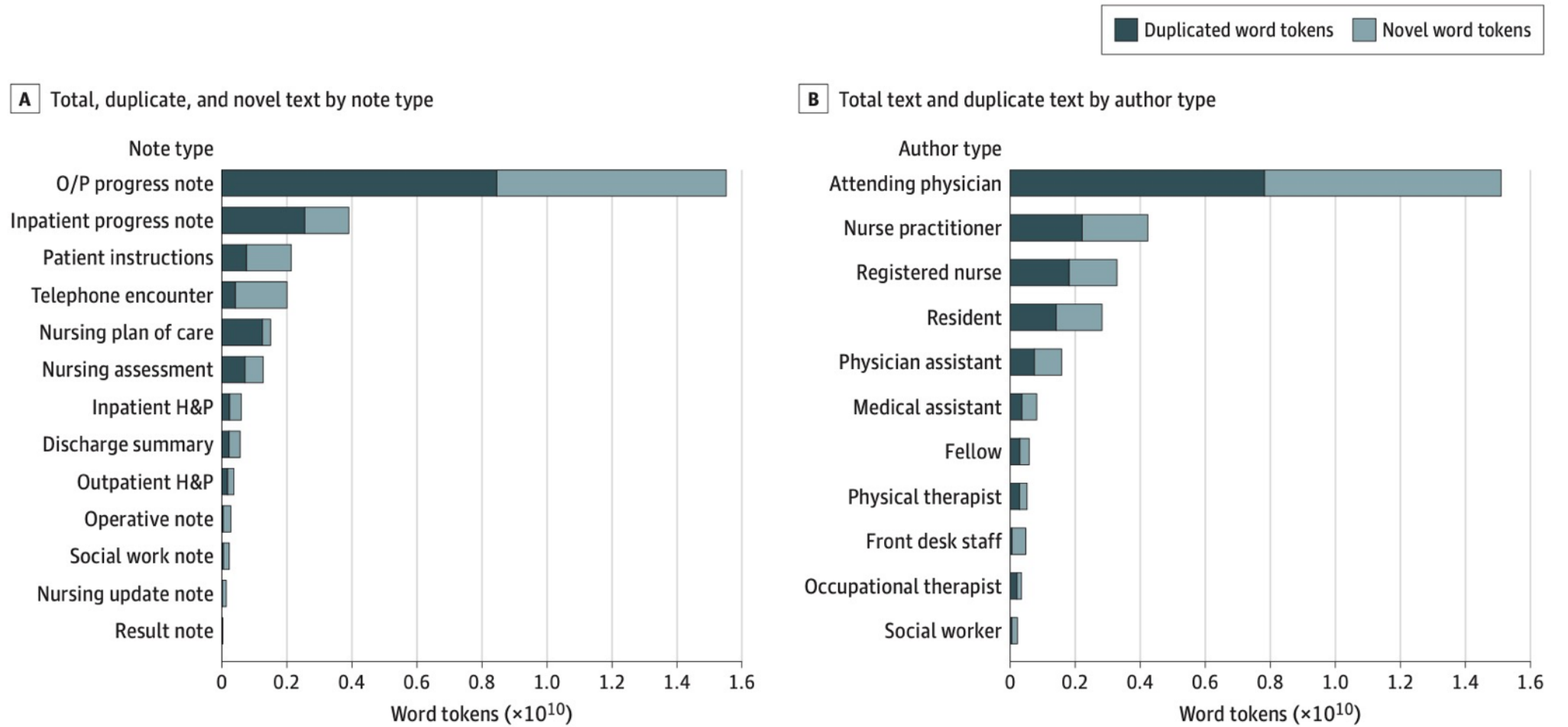
Jackson Steinkamp, MD; Jacob J. Kantrowitz, MD, PhD; Subha Airan-Javia, MD

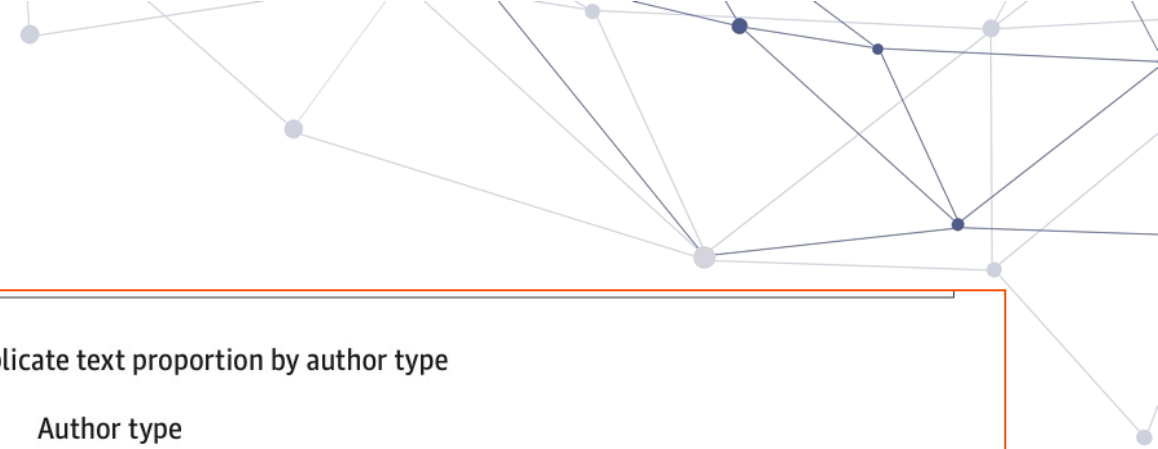
- Cross-sectional analysis of 6 years of the EHR notes corpus at UPenn; looking for 10-word adjacent "word tokens" (repeats)
- 105M notes across 2M patients; Epic and briefly Allscripts
- What are the trends in note length and duplication use
- Look for novel text vs duplicated text and segment it out according to role / note type



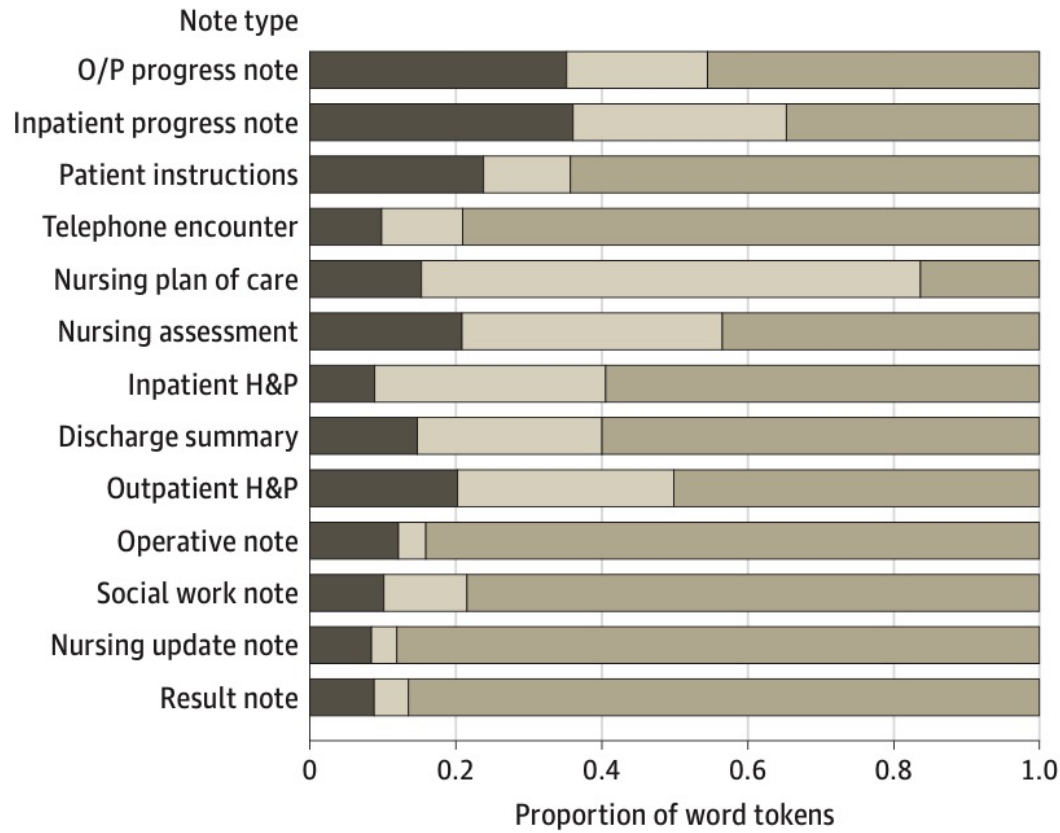


Figure 1. Prevalence of Duplicate Content by Note and Author Type

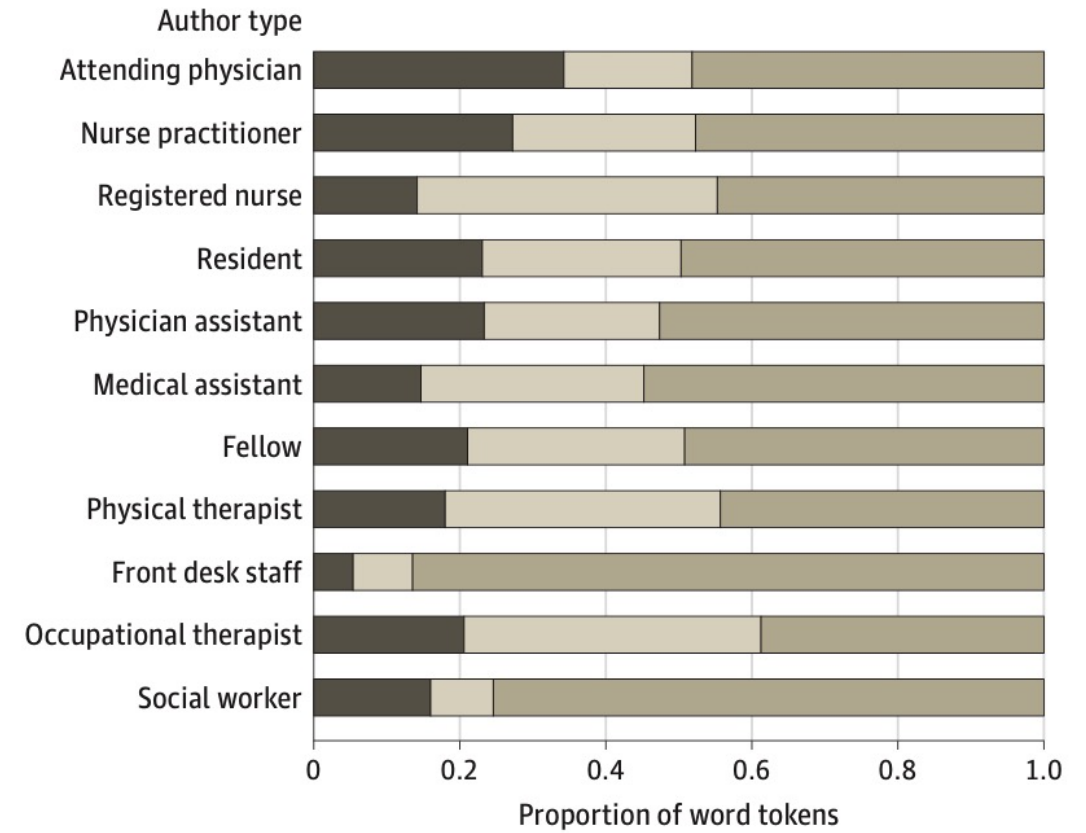


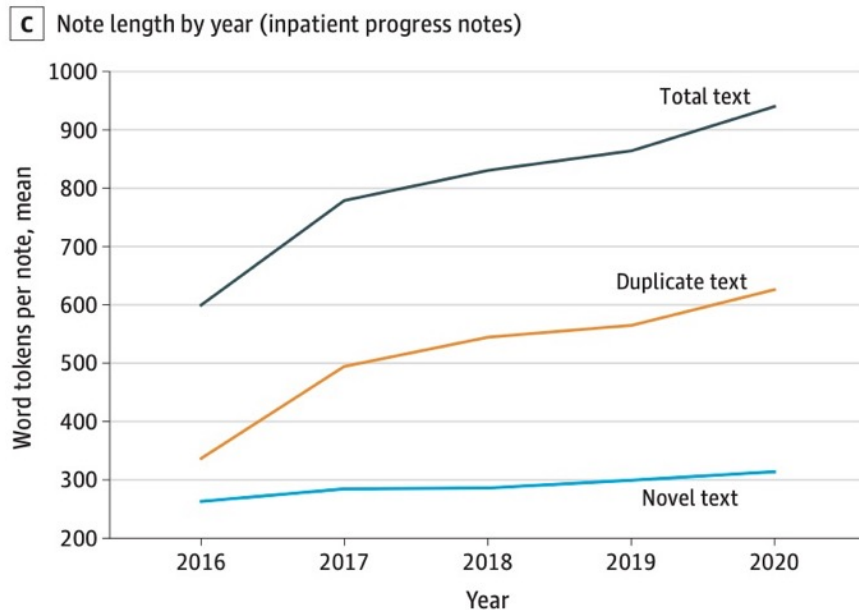
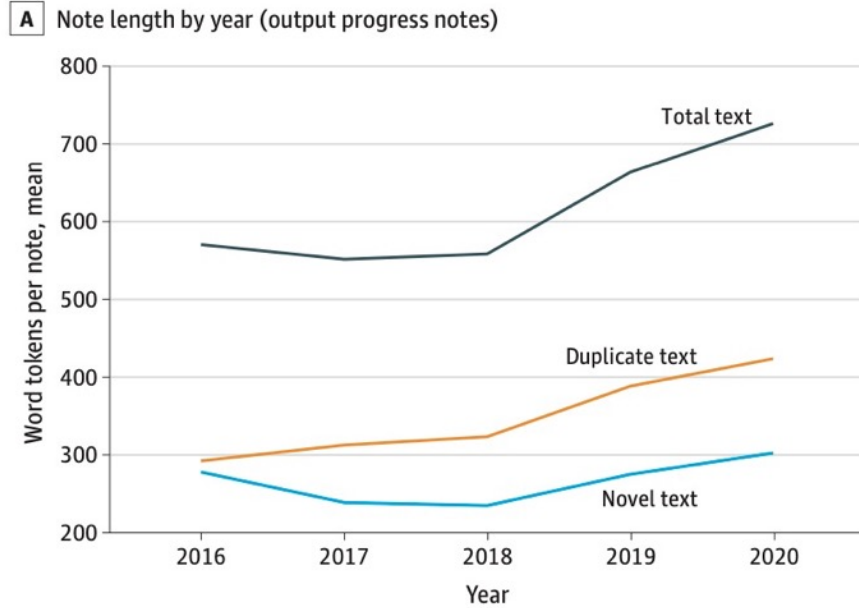


C Duplicate text proportion by note type

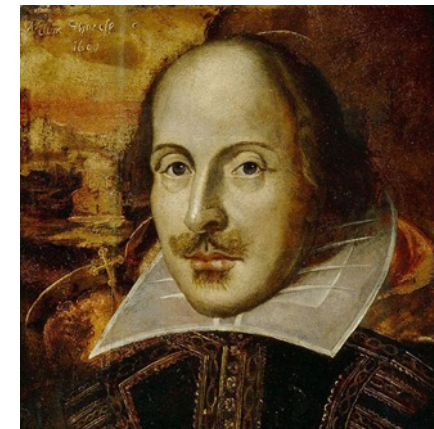


D Duplicate text proportion by author type






- ~50% of content is duplicated
- Duplicated content and note length gets exponentially worse as time goes on
- All of Wikipedia is ~4B words; the corpus here is 8x as large
- Average chart length for a patient is half the length of Shakespeare's Hamlet





Documentation dynamics: Note composition, burden, and physician efficiency

Nate C. Apathy PhD^{1,2}  | Lisa Rotenstein MD, MBA^{3,4} |
David W. Bates MD, MSc^{3,5} | A. Jay Holmgren PhD, MHI⁶

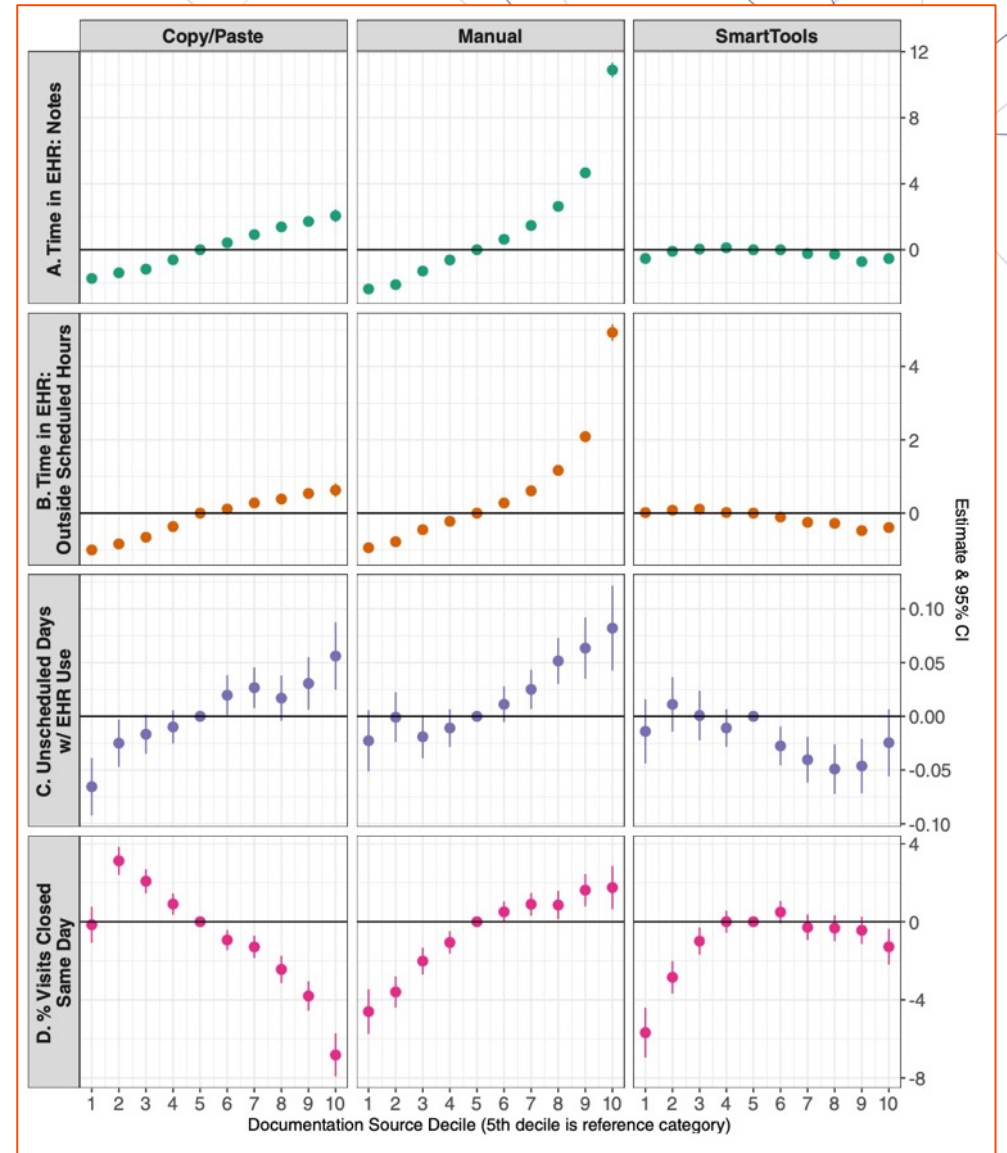
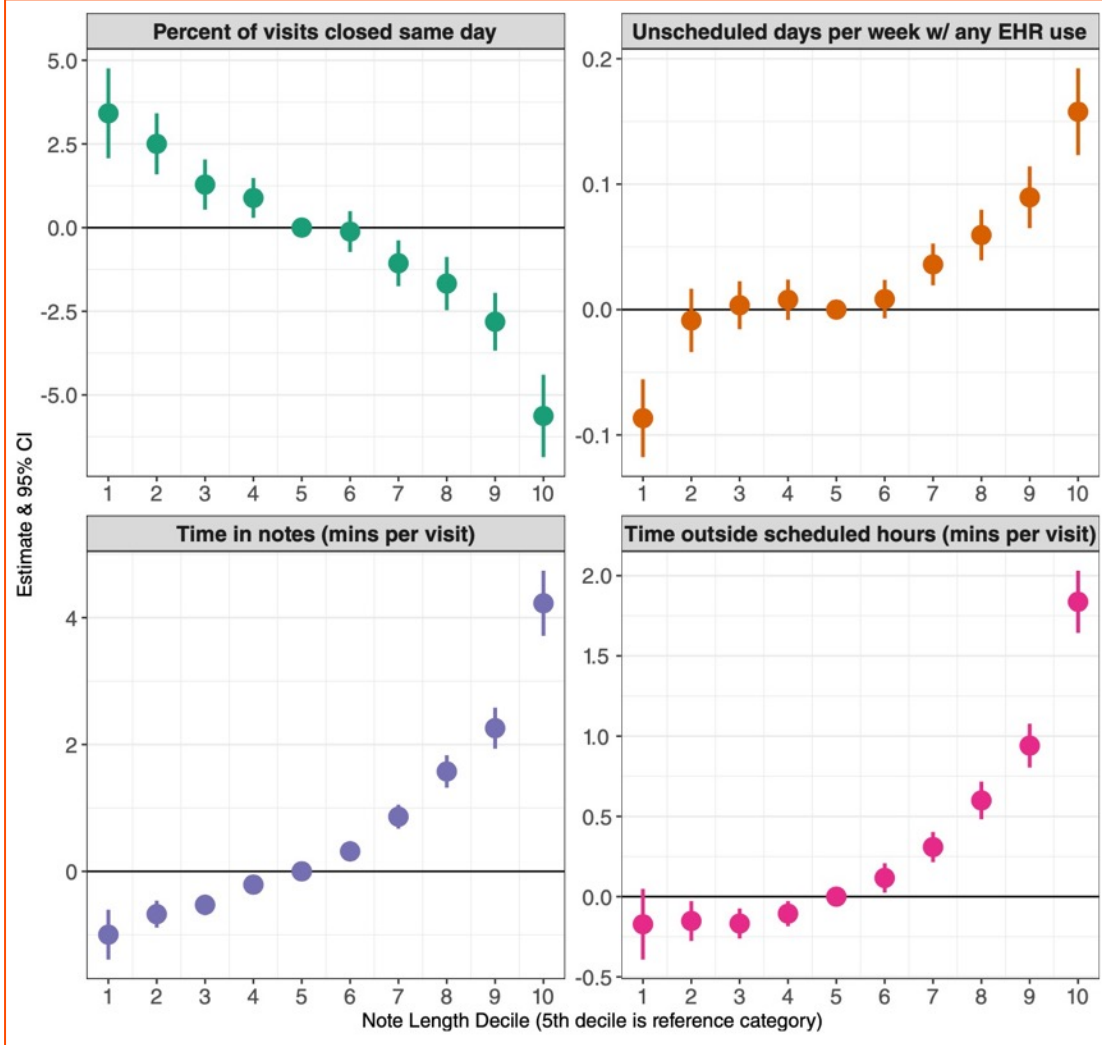


All of Epic OP users Sept 2020 –
May 2021, anonymized using Signal
data

- How does note length correlate with burden and efficiency?
- How does the use of things like copy/paste and smart phrases correlate with length and burnout?
- Does it vary among specialties?
(No)

Efficiency and Burnout as measured by:

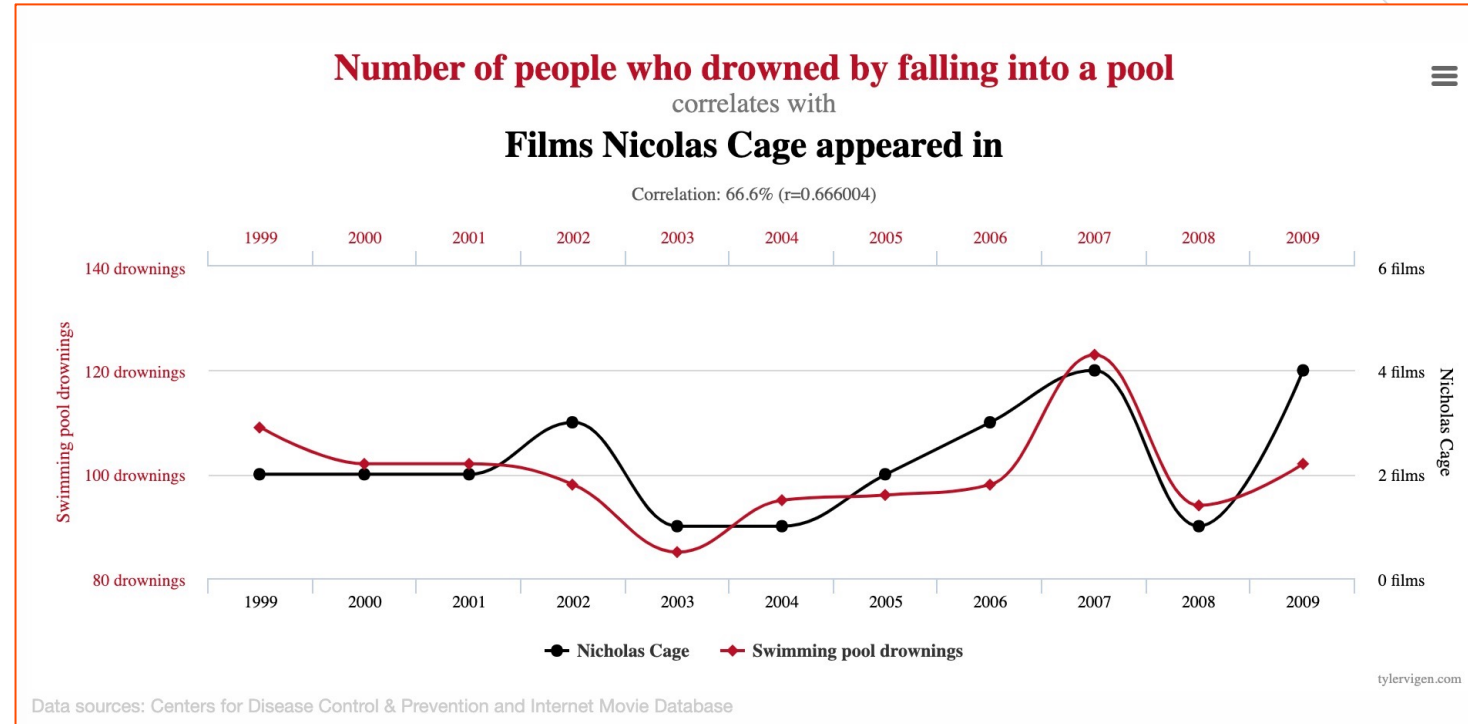
- Time per note
- Percent of visits closed per day
- Unscheduled day with EHR usage
- Time spent outside work hours





Correlation vs Causation ?

- First and largest-scale national analysis of how physician note composition relates to measures of physician burden and efficiency that have been tied to burnout
- Physicians that write the longest notes use the EHR more during off hours and on days off, and close fewer visits in the same day (i.e., experience more burden and less efficient)
- High use of the tools intended to improve documentation efficiency like templated text and copy/paste do not correlate with decreased burden or improved efficiency





Problem Lists and CDS by Bill






Canva

“Stressed out doctor pulling his hair out in front of a computer.”



Research and Applications

A multi-site randomized trial of a clinical decision support intervention to improve problem list completeness

Adam Wright ^{1,2,3,4,5}, Richard Schreiber ⁶, David W. Bates ³, Skye Aaron³,
Angela Ai ³, Raja Arul Cholan⁷, Akshay Desai³, Miguel Divo³, David A. Dorr ⁷,
Thu-Trang Hickman^{3,8}, Salman Hussain³, Shari Just⁵, Brian Koh¹, Stuart Lipsitz³,
Dustin Mcevoy⁴, Trent Rosenbloom ^{1,2}, Elise Russo¹, David Yut-Chee Ting⁹,
Asli Weitkamp^{1,5}, and Dean F. Sittig ¹⁰

CDS to add problems

3 Institutions

3 EHRs

Inpatient/Outpatient

12 Diseases (Adult Medical)

Pre- & Post-CDS problem placement, alerts acceptance, quality measures

Alert to Add a Problem

The screenshot shows a software interface for a 'BestPractice Advisory - Phsiqmtest,Chfimp'. It features a yellow warning banner with a triangle icon and the text: 'Patient has had a BNP > 400 pg/mL and is taking at least one medication involved in the management of heart failure, but heart failure is not on the problem list. Add heart failure to problem list if appropriate.' Below the banner, it states 'Last BNP=453 Collected on 1/27/2017'. There are two buttons: 'Add Problem' (highlighted in blue) and 'Do Not Add'. To the right of these buttons is the text 'Congestive heart failure > Edit details (Share with patient)'. Below this is a section for 'Acknowledge Reason' with a text input field and two buttons: 'Patient does not have heart failure' and 'Defer'. At the bottom right of the advisory box are two buttons: 'Accept' (with a green checkmark icon) and 'Dismiss'.

Figure 1. Screenshot of the IQ-MAPLE intervention, for CHF, at MGB.

CDS to add problems

Table 2. Proportion of missing problems added, by condition and arm

Condition	Control	Intervention	<i>P</i>
Asthma	404/23 286 = 1.7%	3164/19 309 = 16.4%	<.0001
Atrial fibrillation	173/9873 = 1.8%	1562/9774 = 16.0%	<.0001
COPD	150/10 496 = 1.4%	931/9004 = 10.3%	<.0001
CHF	88/15 197 = 0.6%	1821/15 597 = 11.7%	<.0001
CAD	236/17 319 = 1.4%	1654/15 261 = 10.8%	<.0001
Hyperlipidemia	3505/110 643 = 3.2%	36 750/112 793 = 32.6%	<.0001
Hypertension	2082/79 358 = 2.6%	14 463/79 401 = 18.2%	<.0001
Myocardial infarction	28/9650 = 0.3%	825/8912 = 9.3%	<.0001
Sickle cell	16/754 = 2.1%	136/729 = 18.7%	<.0001
Sleep apnea	93/13 228 = 0.7%	1417/10 712 = 13.2%	<.0001
Stroke	78/7962 = 1.0%	812/6347 = 12.8%	<.0001
Tuberculosis	28/1051 = 2.7%	242/993 = 24.4%	<.0001
Total	6881/298 817 = 2.3%	63 777/288 832 = 22.1%	<.0001

Problem Placement = very robust
Compliance ~ 22%

Effect of a better problem list on quality measures

Table 3. Clinical outcomes

Condition	Control	Intervention	P
CAD			
Anti-HLD Meds	514/768 = 66.9%	545/755 = 72.2%	.030
Anti-platelet Meds	820/1105 = 74.2%	846/1130 = 74.9%	.757
BP Control	289/371 = 77.9%	287/381 = 75.3%	.456
LDL Control	369/768 = 48.0%	344/755 = 45.6%	.358
LDL Testing	459/768 = 59.8%	438/755 = 58.0%	.520
Hyperlipidemia (HLD)			
Anti-HLD Meds	24 018/28 488 = 84.3%	26 472/31 355 = 84.4%	.701
LDL Control	7412/28 488 = 26.0%	8134/31 355 = 25.9%	.839
LDL Testing	10 583/28 488 = 37.1%	11 738/31 355 = 37.4%	.474
Hypertension (HTN)			
Anti-HTN Meds	5959/7920 = 75.2%	6598/8684 = 76.0%	.276
BP control	4983/7919 = 62.9%	5388/8684 = 62.0%	.249
MI			
Anti-HLD Meds	284/457 = 62.1%	298/486 = 61.3%	.846
Anti-platelet Meds	572/755 = 75.8%	642/831 = 77.3%	.521
LDL Control	181/457 = 39.6%	179/486 = 36.8%	.418
LDL Testing	234/457 = 51.2%	237/486 = 48.8%	.494
Stroke			
Anti-HLD Meds	218/408 = 53.4%	288/480 = 60.0%	.057
Anti-platelet Meds	348/614 = 56.7%	444/726 = 61.2%	.108

Other Problem List Studies for Context: Adding Problems with Ordering Meds

The screenshot shows a 'New Prescription' form with the following fields and options:

- Add New Drug:** [Text Input]
- Print Blank Rx:** [Print Icon]
- Select:** All None [Save] [Save and Print] [Delete]
- Table:**

<input type="checkbox"/>	Drug	Posology	Quantity/Duration	Indication(s)	Stop/Change Reason
<input type="checkbox"/>	GABAPENTIN 100MG CAPSULE Sample: <input type="checkbox"/>	1.00 CAPSULE tid	30 Day(s) 6 Refills Qty: 90.00 Auto: <input checked="" type="checkbox"/>	[Dropdown Menu] Aggressive/Antisocial Behavior Bipolar affective disorder Diabetic Neuropathy Epilepsy Essential Tremor Fibromyalgia Lateral Amyotrophic Sclerosis Migraine Neurogenic Pain Nonorganic sleep disorders Other sleep disorders Parkinson's disease Postherpetic Neuralgia Reflex Dystrophy Restless Legs Syndrome Trigeminal Neuralgia Vasomotor Symptoms Of Menopause	
- Note:** [Text Input]

Indication Placement = very robust
Compliance > 95% (PCPs, outpatient, Canada)

Adding Problems with homegrown CDS

Figure 1 Screenshot of problem inference alerts.

Problem List Suggestion

Based on patient's clinical and billing data, the patient may have the following problems. Upon save, checked items will be added to the problem list. Unchecked items will not be added, and you will not be prompted again. + Expand All

Add	Problem Description	
<input checked="" type="checkbox"/>	Coronary arteriosclerosis: Patient is taking a platelet aggregation inhibitor and has been billed at least once for CAD.	<input type="text" value="Enter Customizable Description..."/>
<input checked="" type="checkbox"/>	Diabetes mellitus: Patient has a HbA1c >= 7.0%.	<input type="text" value="Enter Customizable Description..."/> + Related terms
<input checked="" type="checkbox"/>	Hypertensive disorder: Patient has been billed for hypertension and is on an antihypertensive agent.	<input type="text" value="Enter Customizable Description..."/> + Related terms
<input checked="" type="checkbox"/>	Hypothyroidism: Patient is on thyroid hormone.	<input type="text" value="Enter Customizable Description..."/>
<input checked="" type="checkbox"/>	Osteoporosis: Patient has been billed at least twice for osteoporosis or osteopenia.	<input type="text" value="Enter Customizable Description..."/>
	or	
<input type="checkbox"/>	Osteopenia: Patient has been billed at least twice for osteoporosis or osteopenia.	<input type="text" value="Enter Customizable Description..."/>
<input checked="" type="checkbox"/>	Chronic renal impairment: Patient has at least three low GFRs, and their most recent GFR is also low.	<input type="text" value="Enter Customizable Description..."/> + Related terms
	or	
<input type="checkbox"/>	Chronic renal failure syndrome: Patient has at least three low GFRs, and their most recent GFR is also low.	<input type="text" value="Enter Customizable Description..."/> + Related terms

Explanations Save Cancel

Problem Placement = very robust
Compliance ~ 41% (inpatient/outpatient)

Adding Problems with Ordering Meds

BestPractice Advisory - [REDACTED]

Missing Diagnosis (1)

 Medication errors are less frequent when problem lists include the related diagnosis.






Please select an indication below to add to [REDACTED] Problem List for this medication.

Optional: Please [provide feedback](#) on this alert. Thank you for helping refine our approaches for prescribing safely!

Remove the following orders?

Remove	Keep	 benazepril (LOTENSIN) tablet 20 mg 20 mg, Oral, DAILY, First Dose tomorrow at 0900
--------	------	---

Apply the following?

Add Problem	Do Not Add	Hypertension  Edit details (Hospital problem)
Add Problem	Do Not Add	Coronary artery disease  Edit details (Hospital problem)
Add Problem	Do Not Add	Past myocardial infarction  Edit details (Hospital problem)
Add Problem	Do Not Add	Chronic kidney disease  Edit details (Hospital problem)
Add Problem	Do Not Add	Congestive heart disease (CMS-HCC)  Edit details (Hospital problem)

Problem Placement = very robust

Compliance ~ 50-80% (function of EHR, Med, Venue)

Adding Problems with CDS

EHR	Location	Trigger Logic	Compliance	Setting
MOXXIE	Quebec, Canada	During Med Order	~95%	Ambulatory PCPs, non-coded indications
Cerner	Univ Illinois Chicago	During Med Order	~55-75%	All
EPIC	Northwestern, Chicago	During Med Order	~50%	Ambulatory/Inpatient
Allscripts	New York Presbyterian	During Med Order	~80%	Inpatient
Homegrown	Brigham and Women, Boston	Sign Note	~41%	Ambulatory
EPIC	MGB, Boston	Chart Open	~20%	Ambulatory
EPIC	Oregon Health	Chart Open	~20%	Ambulatory
Homegrown	Vanderbilt, Nashville	Navigator	~20%	Ambulatory/Inpatient
Allscripts	Holy Spirit, PA	Problem List	~20%	Inpatient

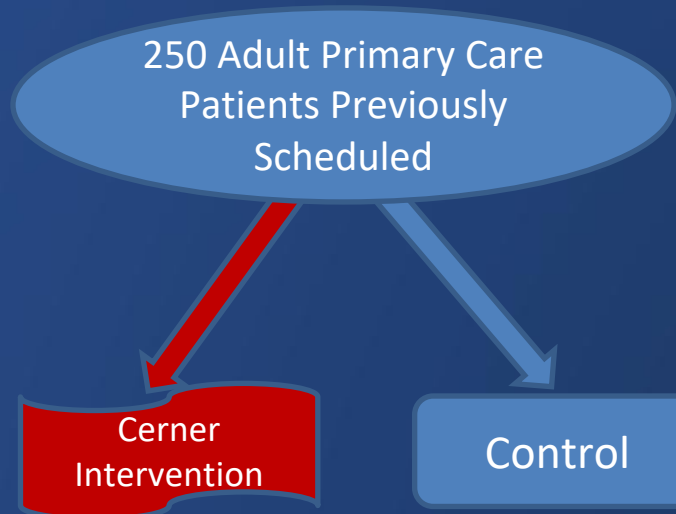
Indication Placement = All very robust
Compliance is variable, depends on triggers, EHRs?

Original Investigation | Health Informatics

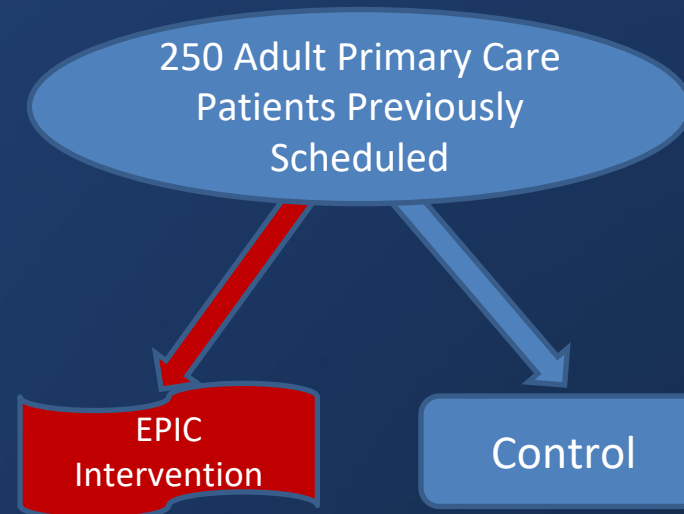
Effect of Electronic Health Record Clinical Decision Support on Contextualization of Care A Randomized Clinical Trial

Saul J. Weiner, MD; Alan Schwartz, PhD; Frances Weaver, PhD; William Galanter, MD, PhD; Sarah Olender, MS, RDN; Karl Kochendorfer, MD; Amy Binns-Calvey, BA; Ravisha Saini, BA; Sana Iqbal, BS, BA; Monique Diaz, MD; Aaron Michelfelder, MD; Anita Varkey, MD

UI Health (Int Med & Fam Med)



Loyola (Int Med & Fam Med)



Contextual Red Flags and Contextual Errors

Hypothetical Example

Red Flag (objective): A1C 4 months ago was 6.9%, at visit it is now 8.5%

Red Flag (Portal/Survey): *“Trouble paying for meds”*

Probing: Clinician asks patient about this issue. Pt reports that the ozempic is not covered anymore by their insurance and is not taking it.

Contextualized Care Plan: Patient switched to Trulicity as it is covered. Advised patient to switch. and/or referred to PharmD to discuss coverage issues

Red Flag Outcome: 6 months later, recent A1C is 7.2 %

Contextual Error: No probing is done and patient is given an Rx for another medicine to add to Ozempic which they are not taking at this time.

Integrating Contextual Factors using CDS to reduce Contextual Error

CDS Integrating into clinic work-flow (MA, RN, PharmD, Social Work, physicians) based on data from Portal/Survey and objective elements from HER

- Interruptive alerts, actionable and informative
- Automated system orders and communication
- Automated informative text

-Outcomes: 1° Resolution of contextual *red flags* at 6 months
2° Proportion of *red flags probed*, Proportion *addressed* in note

-Measurements: recorded and transcribed visits, manual/automated chart review of orders
note and visit text analysis for “probing” and “addressing” *red flags*

Types of Data integrated into workflow from EHR & Survey

Difficulty with: transportation
carrying out healthcare related tasks
living situation affecting health
insurance

Medication issues: cost, forgetting, taking (ex. Insulin),
polypharmacy

EHR Data: BP, A1C, Missed Appointments, PHQ-2, PHQ-9
ED, Urgent Care visits, polypharmacy

Openchart with Contextualized Care Box (CCB)

Discern: Open Chart - TENTH FLOOR, TEST (1 of 1)



This patient is enrolled in the Contextualized Care study which you and the patient have consented for.

Useful Information about this patient may be contained in the Contextualized Care Box (CCB). If you use the clinic note templates (AA Auto Clinic Note, RETURN PATIENT or MEDICINE OUTPATIENT CLINIC NOTE)

You will be provided the CCB automatically in your note. Otherwise you may use the zzCCB template to add it to your note.

The following actions have been automatically generated on behalf of your patient based on contextual factors:

Social Work Consult to assist with transportation

MA pool notified to assist patient in remembering appointments

MA pool notified to connect patient with financial counseling

Social Work Consult to assist with medical costs

Social Work Consult to assist with medical equipment

If you have any questions, please contact Dr. Galanter, Dr. Kochendorfer, or Dr. Weiner

OK

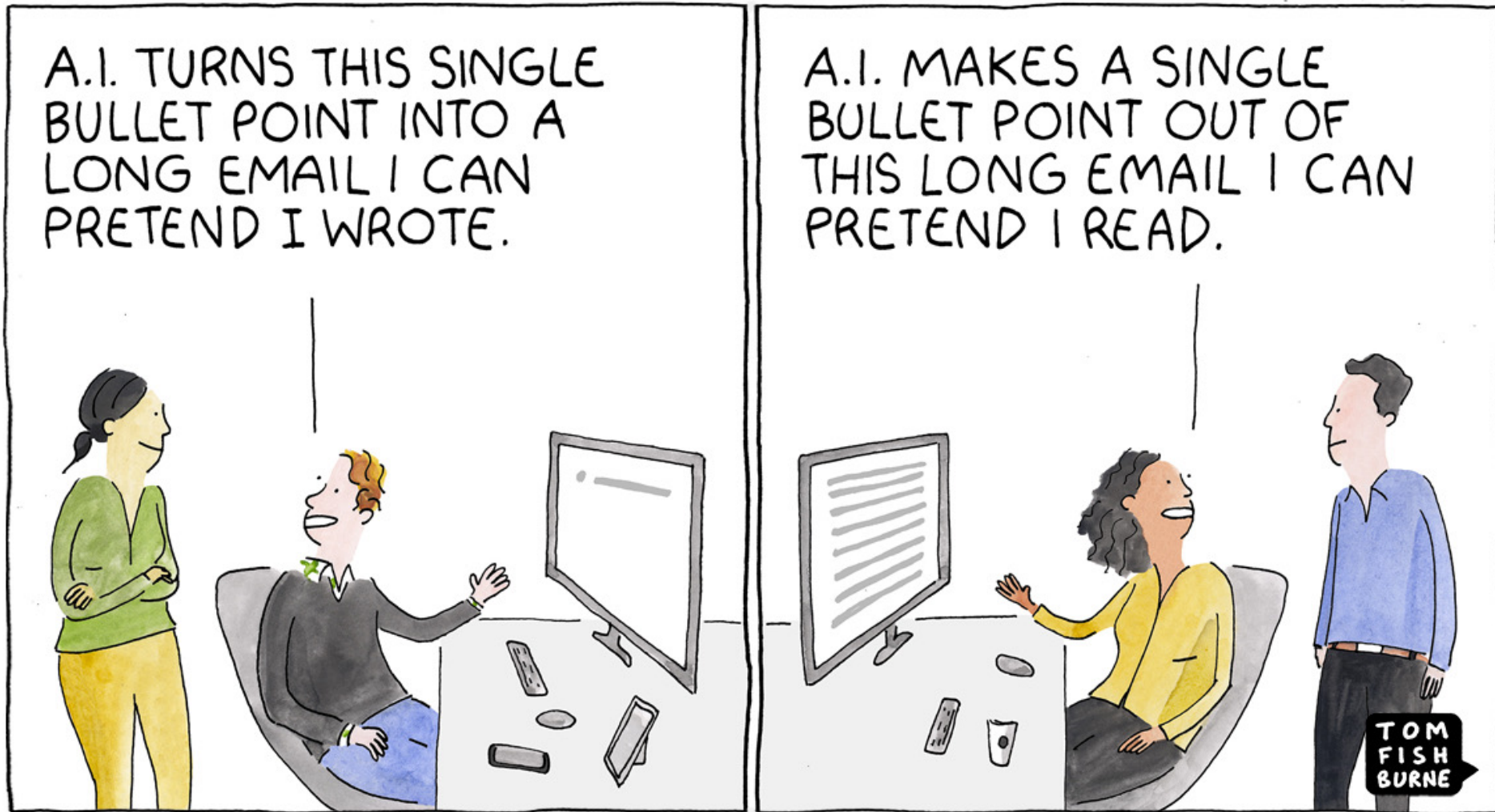
Integrating Contextual Factors using CDS to reduce Contextual Error

Table 4. Patient Outcomes, Clinician Probing, and Clinician Contextual Care Planning by Study Group

	Effect size, adjusted aOR (95% CI) ^a	P value
Outcome: improvement or resolution of red flags at 4-6 mo, adjusted for whether clinician incorporated contextual factor	0.96 (0.57-1.63)	.88
Probing: clinician probes contextual red flags	2.12 (1.14-3.93)	.02
Planning: clinician incorporates contextual factors into care plan	2.67 (1.32-5.41)	.006



Transition Time - The InBox Section





RESEARCH LETTER

Association Between Billing Patient Portal Messages as e-Visits and Patient Messaging Volume

- New billing rules allowed for asynchronous communications to be billed (5min of time within a week)
- Messaging has effectively doubled since 2019; study 2021-2022
- UCSF kicked off initiative
- Patients didn't opt-in; switched to allow the providers to decide when it met criteria and then generate a bill
- Let's see what happens to message volume, who's billing, etc

The New York Times

Emailing Your Doctor May Carry a Fee

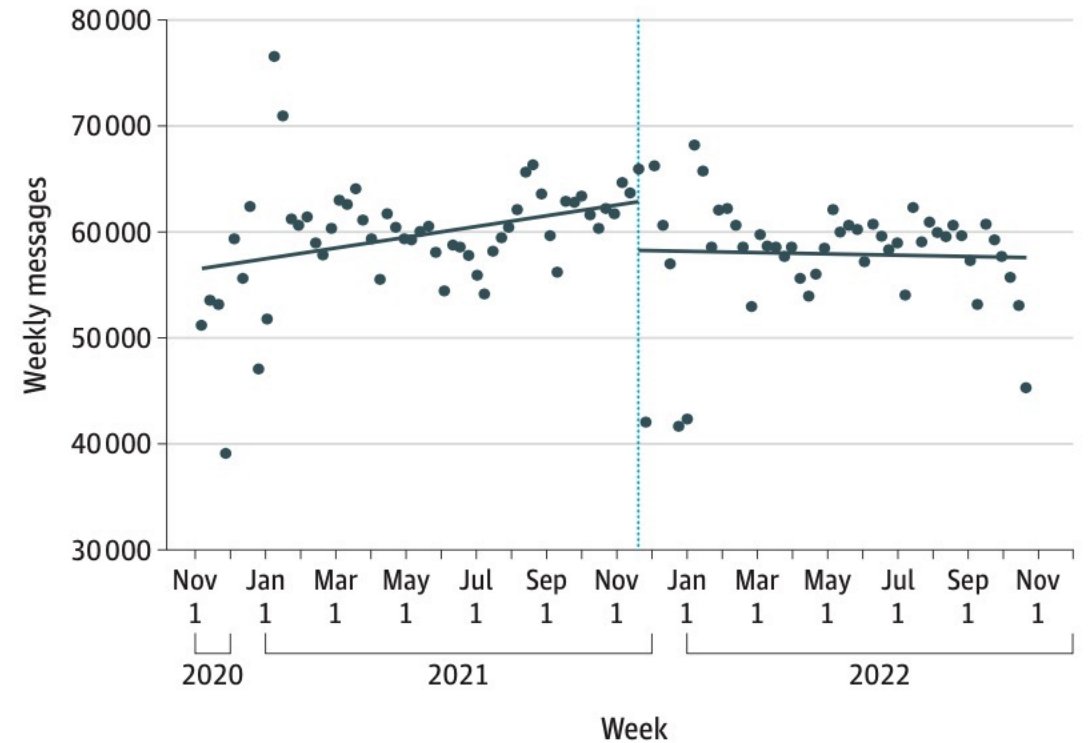
More hospitals and medical practices have begun charging for doctors' responses to patient queries, depending on the level of medical advice.





- No one was making any real money here (billed \$470k out of \$6B revenue)
- Only 1.5% of message threads were billed
- The dip in messages is concerning though
- Curious how other organizations are handling the asynchronous billing ?

C Patient messages





Original Investigation | Health Policy

Perspectives of Patients About Immediate Access to Test Results Through an Online Patient Portal

Bryan D. Steitz, PhD; Robert W. Turer, MD; Chen-Tan Lin, MD; Scott MacDonald, MD; Liz Salmi, AS; Adam Wright, PhD; Christoph U. Lehmann, MD; Karen Langford, BBA; Samuel A. McDonald, MD; Thomas J. Reese, PhD; Paul Sternberg, MD; Qingxia Chen, PhD; S. Trent Rosenbloom, MD; Catherine M. DesRoches, DrPH

JAMA
Network | Open™

- “Open Results”
- Immediate release is now the norm (21st Century Cures) but still controversial for some
- Survey actual patients (43k sent / 8k responded) regarding immediate test result availability
 - University of California
 - University of Colorado
 - Vanderbilt
 - University of Texas

Test Types

- COVID
- Blood
- Imaging
- Biopsy
- Genetic





Figure 1. Percentage of Patients at Each Level of Worry, Stratified by Normal vs Not Normal Test Results

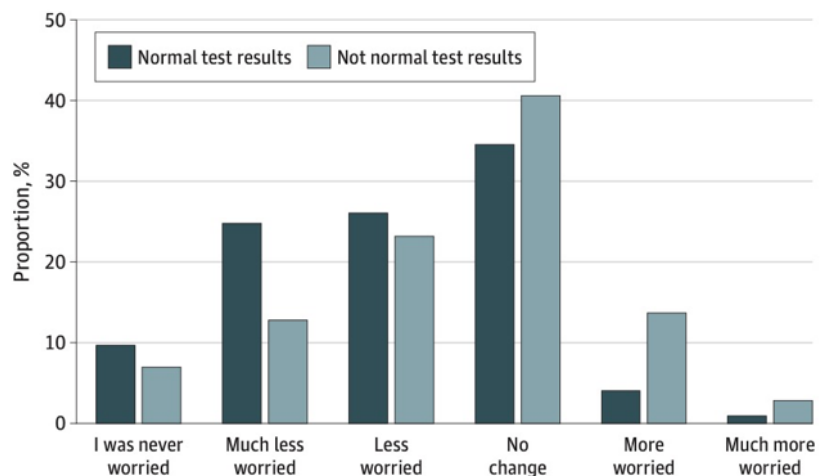


Figure 2. Adjusted Pooled Odds Ratios (ORs) Using a Random-Effects Model of Patient Worry as a Function of Whether a Test Result Was Not Normal

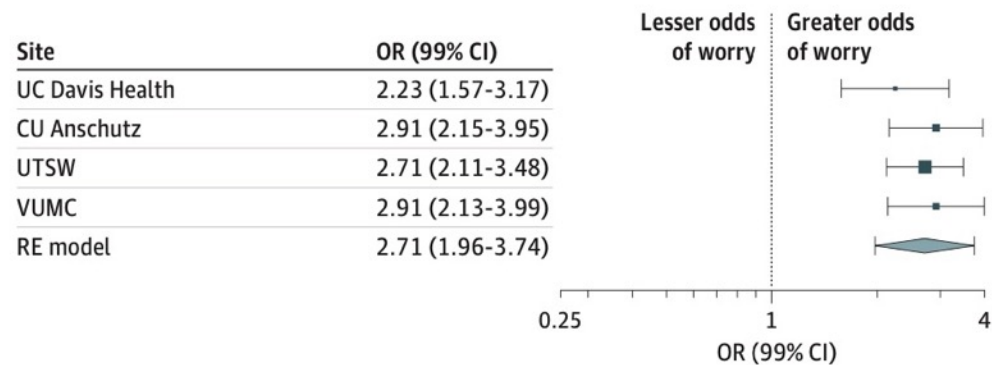


Figure 3. Adjusted Pooled Odds Ratios (ORs) Using a Random-Effects Model Evaluating the Association Between Precounseling Patients About the Reasons for Ordering a Test and Level of Worry

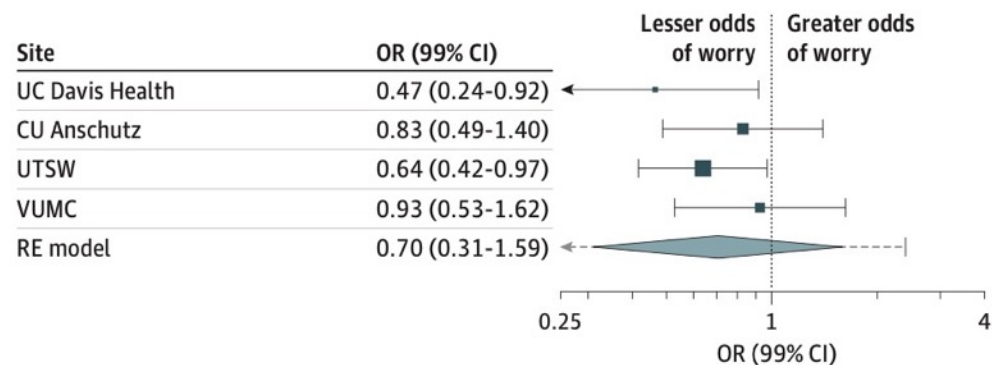




Table 2. Patient Portal Preferences

	Completed responses, No./total No. (%)				
	UC Davis Health	CU Anschutz	UTSW	VUMC	All sites
Future contact preference^a					
Letter in the mail	22/1304 (1.7)	38/1561 (2.4)	56/2903 (1.9)	55/2046 (2.7)	171/7814 (2.2)
Telephone call	203/1304 (15.6)	306/1561 (19.6)	525/2903 (18.1)	411/2046 (20.1)	1445/7814 (18.5)
Text message	444/1304 (34.0)	727/1561 (46.5)	757/2903 (26.1)	542/2046 (26.5)	2091/7814 (26.8)
View on patient portal	1115/1304 (85.5)	1406/1561 (90.1)	2670/2903 (92.0)	1855/2046 (90.7)	7046/7814 (90.2)
Other	68/1304 (5.2)	60/1561 (3.8)	105/2903 (3.6)	67/2046 (3.1)	300/7814 (3.8)
Do not know	13/1304 (1.0)	15/1561 (1.0)	19/2903 (0.7)	17/2046 (0.8)	64/7814 (0.8)
Would like to continue receiving immediately released test results					
Yes	1231/1307 (94.2)	1514/1569 (96.5)	2803/2928 (95.7)	1972/2055 (96.0)	7520/7859 (95.7)
No	42/1307 (3.2)	35/1569 (2.2)	80/2928 (2.7)	44/2055 (2.1)	201/7859 (2.6)
Other	34/1307 (2.6)	20/1569 (1.3)	45/2928 (1.5)	39/2055 (1.9)	138/7859 (1.8)

- Overwhelming preference to continue digital results delivery (text / portal)
- Overwhelming preference to continue "Open Results"; even when the result is abnormal



Original Investigation | Health Informatics

Association of Electronic Health Record Inbasket Message Characteristics With Physician Burnout

Sally L. Baxter, MD, MSc; Bharanidharan Radha Saseendrakumar, MS; Michael Cheung, BS; Thomas J. Savides, MD; Christopher A. Longhurst, MD; Christine A. Sinsky, MD; Marlene Millen, MD; Ming Tai-Seale, PhD, MPH



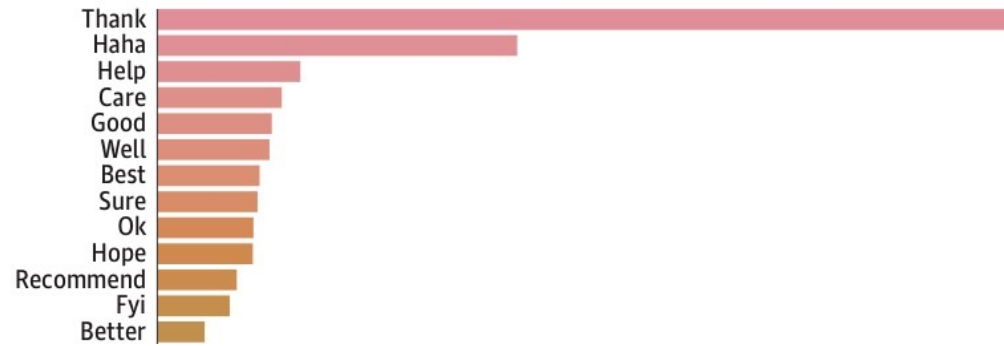
- UCSD; 6 months of Inbasket message data for ~300 providers across multiple specialties
- Does the sentiment of the messages impact self reported burnout scores? How burned out do you feel 1-5 scale
- Sentiment analysis using NLP toolkit "nlkt" and "VADER" to rate the sentiment; extremely positive 1.0 to extremely negative -1.0

- First application of NLP (at the time) to Inbasket messages

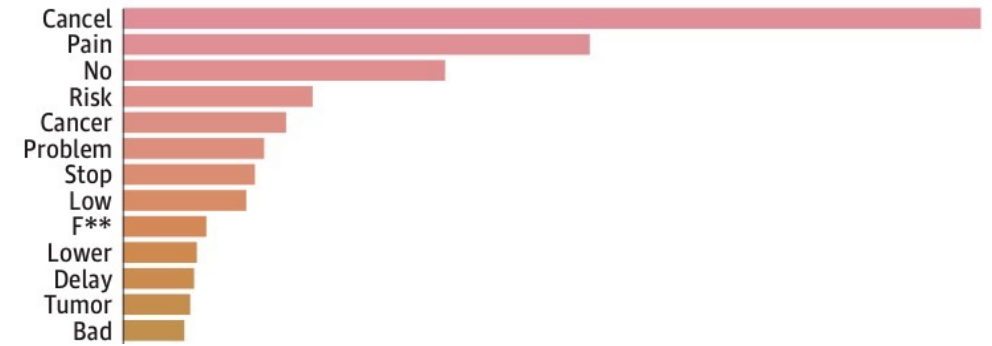




A Patient messages with overall positive sentiment score



B Patient messages with overall negative sentiment score



Fu**

“I am so upset that i was told the blood work would include the gender of the baby. I have been waiting 5 d to find it, and it wasnt even fu**ing tested!!!! What a disappointment in your office and the bullsh** i was told. I will be switching plans because this is sh**!”

“This whole experience makes me want to just say fu** my health. I don't care what's wrong or what happens to me.”

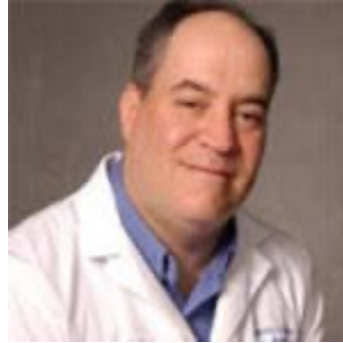
“What the actual fu**! What kind of PCP is this!”

“Are you just put out with what's going on? This is serious too me and I am very concerned about. If this is how you're feeling about my issue that fu** it. You're not the one that is experiencing it!!!”

- No statistically significant correlation between burnout and message sentiment
- “Expletives and violent words represent an opportunity for improving patient engagement, EHR portal design, or filters.”



Transition - CDS Papers from Bill



Bill as Yoda via the ReFace
app



Research and Applications

Using CDS Hooks to increase SMART on FHIR app utilization: a cluster-randomized trial

Keaton L. Morgan ^{1,2}, Polina V. Kukhareva ¹, Phillip B. Warner¹, Jonah Wilkof³, Meir Snyder³, Devin Horton ⁴, Troy Madsen ², Joseph Habboushe³, and Kensaku Kawamoto ¹

<https://ecqi.healthit.gov/tool/cds-hooks>

<https://cds-hooks.hl7.org/1.0/>

Morgan KL, Kukhareva PV, Warner PB, Wilkof J, Snyder M, Horton D, Madsen T, Habboushe J, Kawamoto K. Using CDS Hooks to increase SMART on FHIR app utilization: a cluster-randomized trial. *J Am Med Inform Assoc*. 2022 Aug 16;29(9):1461-1470. doi: 10.1093/jamia/ocac085. PMID: 35641136; PMCID: PMC9382378.

CDS Hooks to increase SMART on FHIR app utilization

- Randomized, 7-month, 70 providers
- CDS “Hooks” integrated to get increased usage of
- 6 medical calculators in a SMART on FHIR medical reference app
- Outcome was the percentage of encounters with App usage

CDS Hooks to increase SMART on FHIR app utilization

Table 4. Percentage of unique interactions where a study calculator was viewed in the control and intervention groups


MDCalc for EHR app use	Percentage of unique interactions with a study calculator viewed (estimate and 95% CI)		Odds ratio	P value
	Control group	Intervention group		
Any study calculator	2.6 (1.5–4.4)	6.0 (3.7–9.6)	2.45 (1.15–5.22)	.02*
Canadian CT head rule	1.9 (1.0–3.7)	3.6 (2.1–6.0)	1.92 (0.79–4.64)	.15
Canadian C-spine rule	0.9 (0.4–2.0)	2.9 (1.6–5.2)	3.38 (1.21–9.42)	.02*
HEART score	3.2 (1.7–5.6)	6.5 (3.9–10.6)	2.15 (0.94–4.89)	.069
PERC rule	4.8 (2.8–8.1)	7.1 (4.2–11.7)	1.52 (0.7–3.32)	.29
Wells' criteria for PE	2.6 (1.4–4.8)	6.2 (3.6–10.4)	2.44 (1.05–5.64)	.038*
Wells' criteria for DVT	1.9 (0.7–5.4)	4.0 (2.2–7.1)	2.11 (0.62–7.26)	.24
Senior EM providers, any study calculator	3.5 (1.9–6.4)	4.6 (2.4–8.6)	1.31 (0.52–3.28)	.57
Junior EM providers, any study calculator	1.2 (0.4–3.5)	8.2 (4.2–15.5)	7.67 (2–29.42)	.003*
All EM residents, any study calculator	1.6 (0.6–4.3)	2.9 (1.2–6.7)	2.11 (0.62–7.26)	.36

CI: confidence interval; C-spine: cervical spine; CT: computed tomography; DVT: deep venous thrombosis; EM: emergency medicine; PE: pulmonary embolism; PERC: pulmonary embolism rule-out criteria.

*P value <.05.

Research and Applications

Interruptive Electronic Alerts for Choosing Wisely Recommendations: A Cluster Randomized Controlled Trial

Vy T. Ho ¹, Rachael C. Aikens², Geoffrey Tso³, Paul A. Heidenreich^{4,5},
Christopher Sharp⁶, Steven M. Asch^{3,5}, Jonathan H. Chen⁷, and Neil K. Shah⁸

-Multisite, randomized, controlled

Interruptive Alerts to Choose Wisely

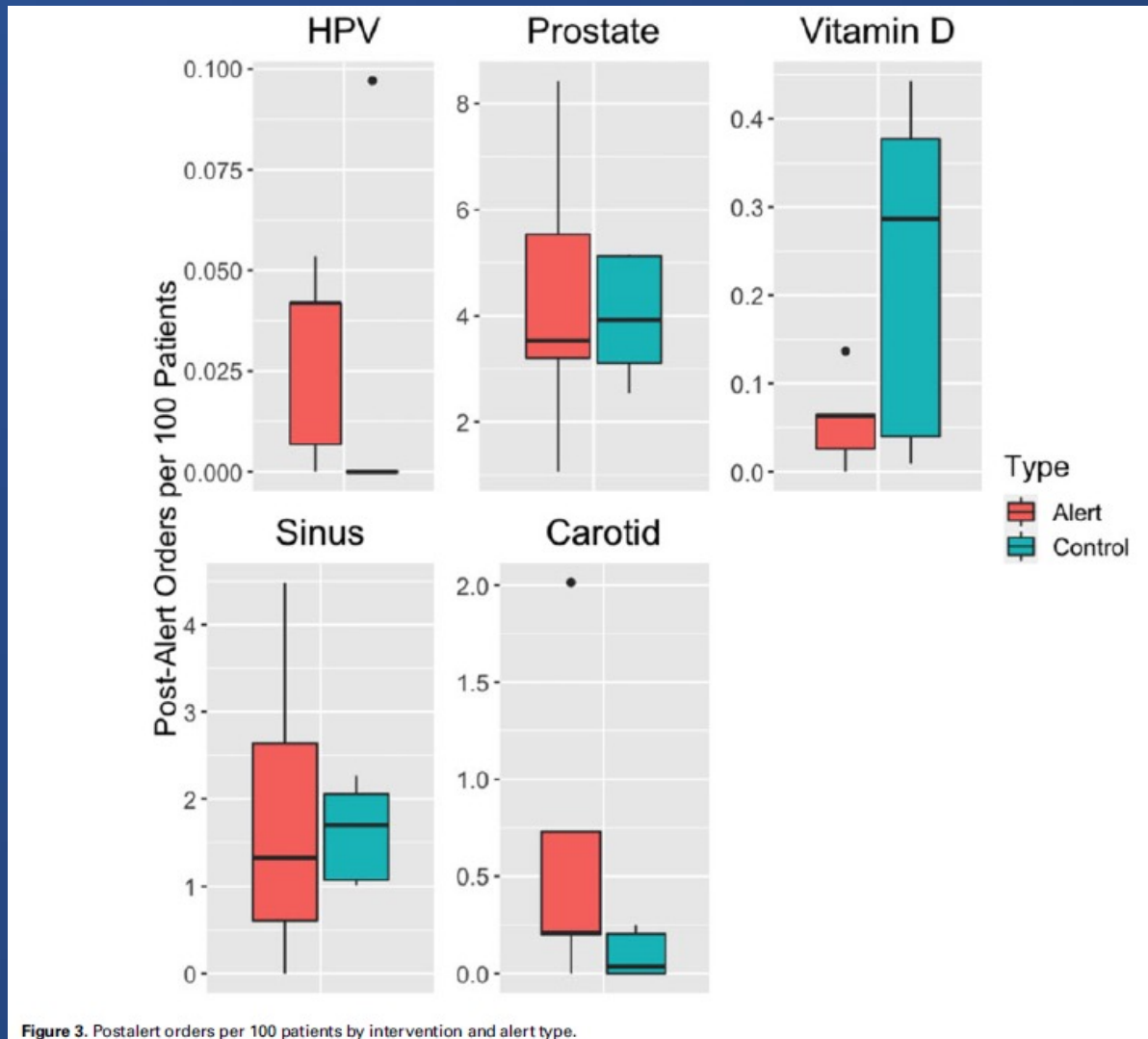





Figure 3. Postalert orders per 100 patients by intervention and alert type.

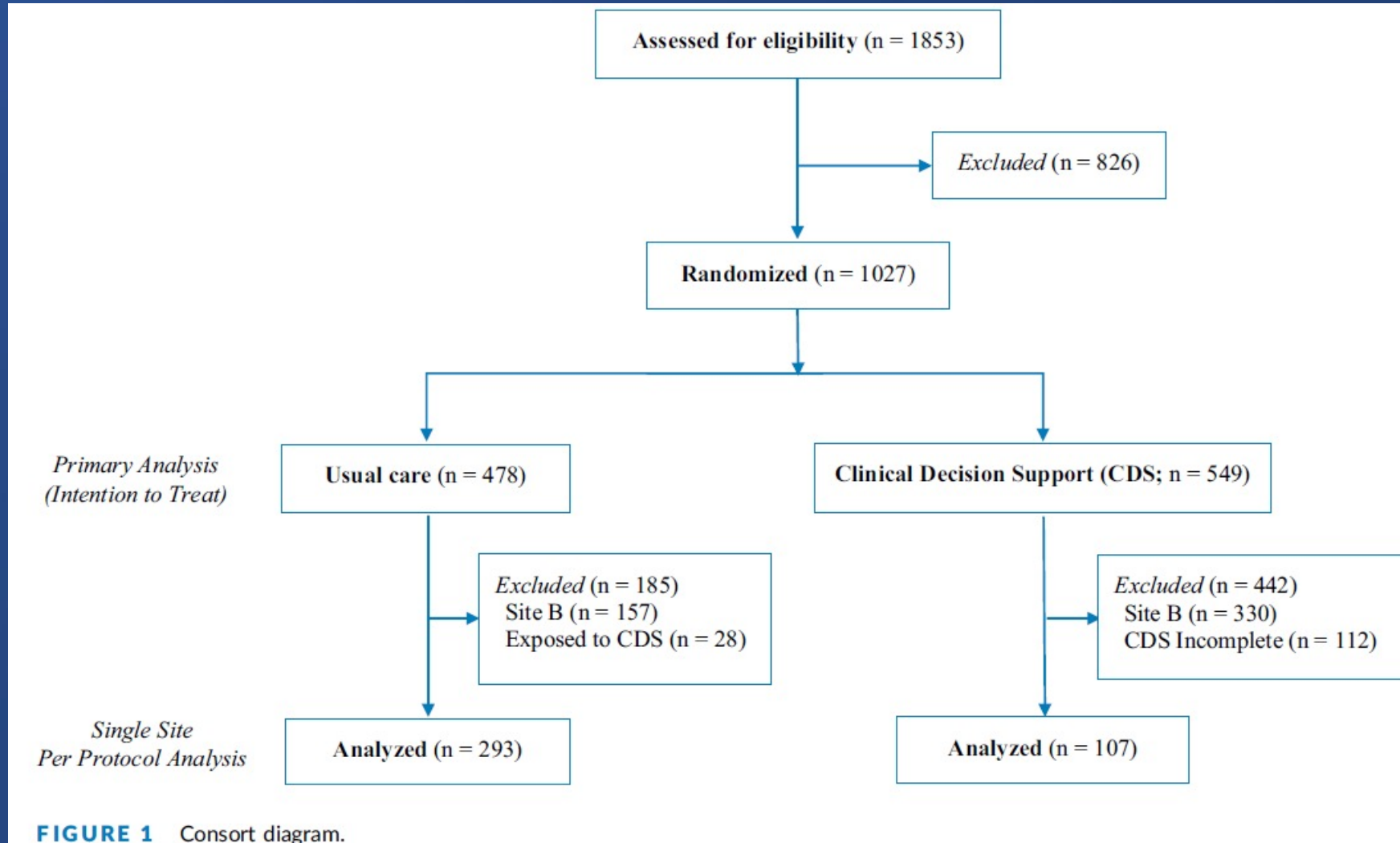
None statistically significant

Antibiotic clinical decision support for pneumonia in the ED: A randomized trial

Derek J. Williams MD, MPH¹ | Judith M. Martin MD² | Hui Nian PhD¹ |
Asli O. Weitkamp PhD¹ | Jason Slagle PhD¹ | Robert W. Turer MD, MSACI³ |
Srinivasan Suresh MD, MBA²  | Jakobi Johnson¹ | Justine Stassun MS¹  |
Shari L. Just RN, MSN¹ | Carrie Reale RN, MSN¹ | Russ Beebe BA¹ |
Donald H. Arnold MD, MPH¹ | James W. Antoon MD, PhD¹  | Nancy S. Rixe MD² |
Laura F. Sartori MD, MPH⁴ | Robert E. Freundlich MD, MSCI¹ | Krow Ampofo MD⁵ |
Andrew T. Pavia MD⁵ | Joshua C. Smith PhD¹ | Matthew B. Weinger MD, MS¹ |
Yuwei Zhu MD, MS¹ | Carlos G. Grijalva MD, MPH¹

Williams DJ, Martin JM, Nian H, Weitkamp AO, Slagle J, Turer RW, Suresh S, Johnson J, Stassun J, Just SL, Reale C, Beebe R, Arnold DH, Antoon JW, Rixe NS, Sartori LF, Freundlich RE, Ampofo K, Pavia AT, Smith JC, Weinger MB, Zhu Y, Grijalva CG. Antibiotic clinical decision support for pneumonia in the ED: A randomized trial. *J Hosp Med*. 2023 Jun;18(6):491-501. doi: 10.1002/jhm.13101. Epub 2023 Apr 12. PMID: 37042682; PMCID: PMC10247532.

CDS for antibiotics for Pneumonia in the ED



Williams DJ, Martin JM, Nian H, Weitkamp AO, Slagle J, Turer RW, Suresh S, Johnson J, Stassun J, Just SL, Reale C, Beebe R, Arnold DH, Antoon JW, Rixe NS, Sartori LF, Freundlich RE, Ampofo K, Pavia AT, Smith JC, Weinger MB, Zhu Y, Grijalva CG. Antibiotic clinical decision support for pneumonia in the ED: A randomized trial. *J Hosp Med*. 2023 Jun;18(6):491-501. doi: 10.1002/jhm.13101. Epub 2023 Apr 12. PMID: 37042682; PMCID: PMC10247532.

CDS for antibiotics for Pneumonia in the ED

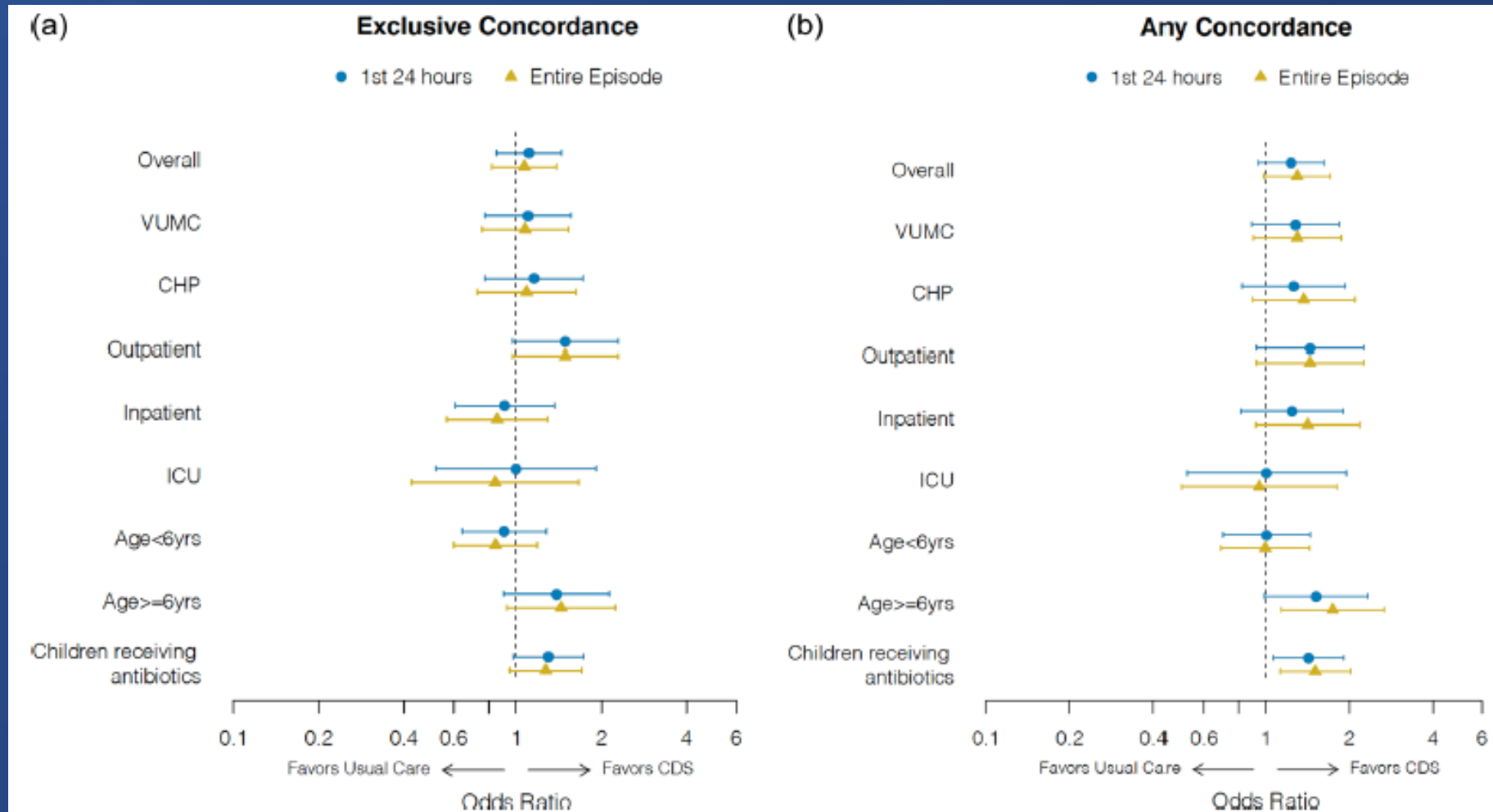


FIGURE 3 Adjusted odds ratios for exclusive and any guideline-concordant antibiotic prescribing during the first 24 h of care and for the entire episode. Forest plots demonstrating adjusted odds ratios with 95% confidence intervals for *exclusive* (a) and *any* (b) guideline-concordant antibiotic prescribing during the first 24 h of care and for the entire episode, overall, and for analyses stratified by enrollment site, initial disposition from the emergency department, and age, and an analysis restricted to those receiving antibiotics. Odds ratios estimated using logistic regression models adjusted for pneumonia severity score (linear predictor) incorporating age, sex, race/ethnicity, SpO₂:FiO₂, HR, RR, and SBP. HR, heart rate; RR, respiratory rate; SBP, systolic blood pressure.

A Pragmatic, Stepped-Wedge, Cluster-controlled Clinical Trial of Real-Time Pneumonia Clinical Decision Support

Nathan C. Dean^{1,2}, Caroline G. Vines³, Jason R. Carr², Jenna G. Rubin⁴, Brandon J. Webb^{5,6}, Jason R. Jacobs⁷, Allison M. Butler⁷, Jaehoon Lee⁷, Al R. Jephson⁷, Nathan Jenson⁸, Missy Walker⁹, Samuel M. Brown^{1,2}, Jeremy A. Irvin¹⁰, Matthew P. Lungren¹¹, and Todd L. Allen¹²

¹Division of Pulmonary and Critical Care Medicine, ⁴Department of Emergency Medicine, and ⁷Office of Research, Intermountain Medical Center, Murray, Utah; ²Division of Respiratory, Critical Care and Occupational Pulmonary Medicine, University of Utah School of Medicine, Salt Lake City, Utah; ³Department of Emergency Medicine, LDS Hospital, Salt Lake City, Utah; ⁵Division of Infectious Diseases, Intermountain Healthcare, Salt Lake City, Utah; ⁶Division of Infectious Diseases and Geographic Medicine and ¹⁰Department of Computer Science, Stanford University, Palo Alto, California; ⁸Department of Emergency Medicine, St. George Regional Medical Center, St. George, Utah; ⁹Department of Emergency Medicine, Utah Valley Regional Medical Center, Provo, Utah; ¹¹Stanford Center for Artificial Intelligence in Medicine and Imaging, Palo Alto, California; and ¹²Center for Quality and Patient Safety, The Queen's Health Systems, Honolulu, Hawaii

Dean NC, Vines CG, Carr JR, Rubin JG, Webb BJ, Jacobs JR, Butler AM, Lee J, Jephson AR, Jenson N, Walker M, Brown SM, Irvin JA, Lungren MP, Allen TL. A Pragmatic, Stepped-Wedge, Cluster-controlled Clinical Trial of Real-Time Pneumonia Clinical Decision Support. *Am J Respir Crit Care Med*. 2022 Jun 1;205(11):1330-1336. doi: 10.1164/rccm.202109-2092OC. PMID: 35258444; PMCID: PMC9873107.

Real-Time Pneumonia CDS in the ED

- Multi-site, single system, single EHR, stepwise, non-blinded, heavy clinician involvement & education
- ePNa-concordant antibiotic prescribing increased from 83.5% to 90.2% (P=0.001)
- The mean time from ED admission to first antibiotic improved from 159.4 (156.9–161.9) to 150.9 (144.1–157.8), or 8.5 minutes (P=0.001).
- 7-day secondary hospital admission was unchanged (5.2% vs. 6.1%).
- ePNa was used by ED clinicians in 67% of eligible patients.

Real-Time Pneumonia CDS in the ED

-Discharge ambulatory from the ED increased from 29.2% to 46.9%



-NNT to prevent an admission of 6! Massive cost-savings.

-30-day all cause MORTALITY was down 38%, OR 0.62 [.49-.79]



-What were the ED docs doing before?

-How did this work?



Transition – Quality of Care Papers by Colin

Canva

“Male doctor in flip flops presenting behind a podium to AMDIS conference of fellow doctors in Ojai California”





The Association of the First Surge of the COVID-19 Pandemic with the High- and Low-Value Outpatient Care Delivered to Adults in the USA



David M. Levine, MD MPH MA^{1,2}, Lipika Samal, MD MPH^{1,2}, Bridget A. Neville, MPH¹, Elisabeth Burdick, MS¹, Matthew Wien, BS¹, Jorge A. Rodriguez, MD^{1,2}, Sandya Ganesan, BS¹, Stephanie C. Blitzer, BA¹, Nina H. Yuan, SM¹, Kenney Ng, PhD³, Yoonyoung Park, ScD³, Amol Rajmane, MD, MBA⁴, Gretchen Purcell Jackson, MD, PhD^{4,5}, Stuart R. Lipsitz, ScD^{1,2}, and David W. Bates, MD, MSc^{1,2,6}

- What happened to core quality measures during the COVID surge?
- 10M adults in the MarketScan and Medicare database looking at period of COVID surge and comparable months in prior year

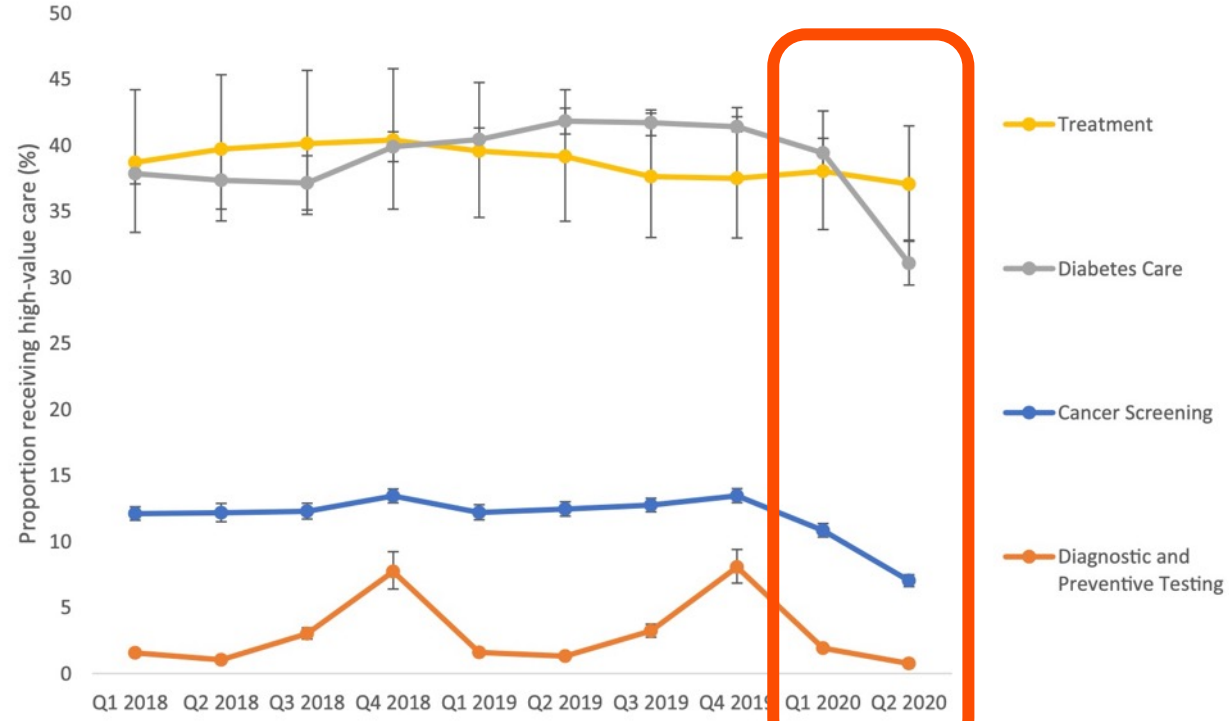
- Commercially insured Americans received less value-care during the COVID surge
 - Diabetes and cancer screening the most
 - Surprisingly (?) is that opioid use for headache and back pain increased
- Can we change healthcare design to compensate during a surge event?
 - Home phlebotomy, mail in blood spots for A1C, kitted cervical screening ?
 - Pharmacy Role



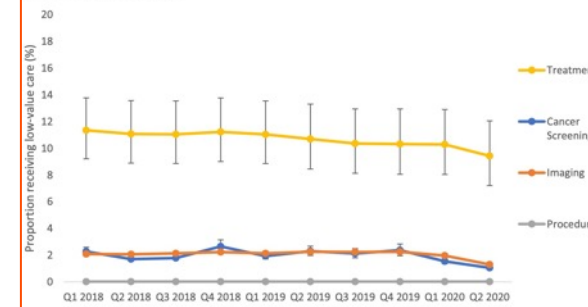
COVID took a hit on quality care measures

High-value care measures			
Cancer screening	10.83	7.02	-3.81
Cervical cancer screening	6.60	4.30	-2.3
Breast cancer screening	12.20	7.66	-4.54
Diagnostic and preventive measures	1.92	0.76	-1.16
Influenza vaccine	4.23	1.67	-2.56
Diabetes care	39.40	31.05	-8.35
Hemoglobin a1c measurement	34.52	27.60	-6.92
Eye exam	7.81	5.19	-2.62
Treatment	38.02	37.05	-0.97
Anticoagulation for atrial fibrillation ^a	2.53	2.49	-0.04
ACEI/ARB for heart failure	45.99	44.59	-1.4
Beta blocker for heart failure	43.73	44.25	0.52
Salicylates and/or platelet aggregation inhibitors for CAD/MI	4.40	4.18	-0.22
Beta blocker for CAD/MI	34.95	34.60	-0.35
Statin for CAD/MI	39.86	38.84	-1.02
Statin for dyslipidemia	31.18	30.37	-0.81
ACEi/ARB for diabetes and hypertension	55.07	53.14	-1.93
Statin for CHD	31.64	30.84	-0.8

b) Trends in high-value care



Trends in low-value care





Association Between Electronic Health Record Time and Quality of Care Metrics in Primary Care

Lisa S. Rotenstein, MD, MBA; A. Jay Holmgren, PhD; Michael J. Healey, MD; Daniel M. Horn, MD; David Y. Ting, MD; Stuart Lipsitz, PhD; Hojjat Salmasian, MD; Richard Gitomer, MD; David W. Bates, MD, MSc

- Cross-sectional study of PCPs at MG and BWH in 2021
- EHR time measures using Epic Signal data
 - Overall
 - After Hours
 - Early AM
 - Weekend Time
 - Time on Notes / correspondence / inbasket review / results review
- Measure correlation with quality
 - BP control
 - A1C control
 - Screening tests
 - Lipid control
- Control for FTE
- Calculate improvements in 15min increments “for every additional 15min spent you would improve by x amount”



- More time in EHR means better metric achievement
- “ These analyses suggest that time spent on in-basket and clinical review may particularly influence quality outcomes, with benefits largely concentrated among PCPs with lower clinical FTEs and panel sizes.”

Table 4. Adjusted Estimated Differences in PCPs' Panel-Level Percent Achievement of Metric Targets per Each Additional 15 Minutes of Daily EHR Time (N = 291)^a

EHR time category	Percentage of panel meeting metric target, β (95% CI)									
	HbA _{1c} control	P value ^b	Hypertension control	P value ^b	Breast cancer screening	P value ^b	Lipid management in established CVD	P value ^b	Diabetes screening	P value ^b
Total daily time	0.58 (0.32 to 0.84)	<.001	0.52 (0.33 to 0.71)	<.001	0.28 (0.05 to 0.52)	.03	0.14 (-0.10 to 0.38)	.54	0.004 (-0.15 to 0.15)	.96
Time outside scheduled hours	0.66 (0.31 to 1.00)	.001	0.60 (0.40 to 0.81)	<.001	0.37 (0.08 to 0.65)	.03	0.21 (-0.09 to 0.52)	.54	-0.06 (-0.21 to 0.09)	.72
Pajama time	0.24 (-0.02 to 0.50)	.07	0.003 (0.001 to 0.004)	.001	0.19 (0.02 to 0.36)	.03	0.03 (-0.24 to 0.30)	.83	-0.04 (-0.16 to 0.08)	.72
Clinical review time	1.64 (0.49 to 2.78)	.006	1.19 (0.41 to 1.98)	.003	-0.17 (-1.21 to 0.88)	.76	-0.28 (-1.18 to 0.62)	.81	0.22 (-0.36 to 0.80)	.72
Notes time	0.64 (0.21 to 1.07)	.006	0.58 (0.26 to 0.89)	.001	0.43 (0.02 to 0.83)	.048	0.06 (-0.45 to 0.58)	.83	-0.06 (-0.27 to 0.16)	.74
In-basket time	2.26 (1.05 to 3.48)	.001	1.65 (0.83 to 2.47)	<.001	1.26 (0.51 to 2.02)	.006	0.57 (-0.42 to 1.57)	.54	-0.27 (-0.99 to 0.45)	.72

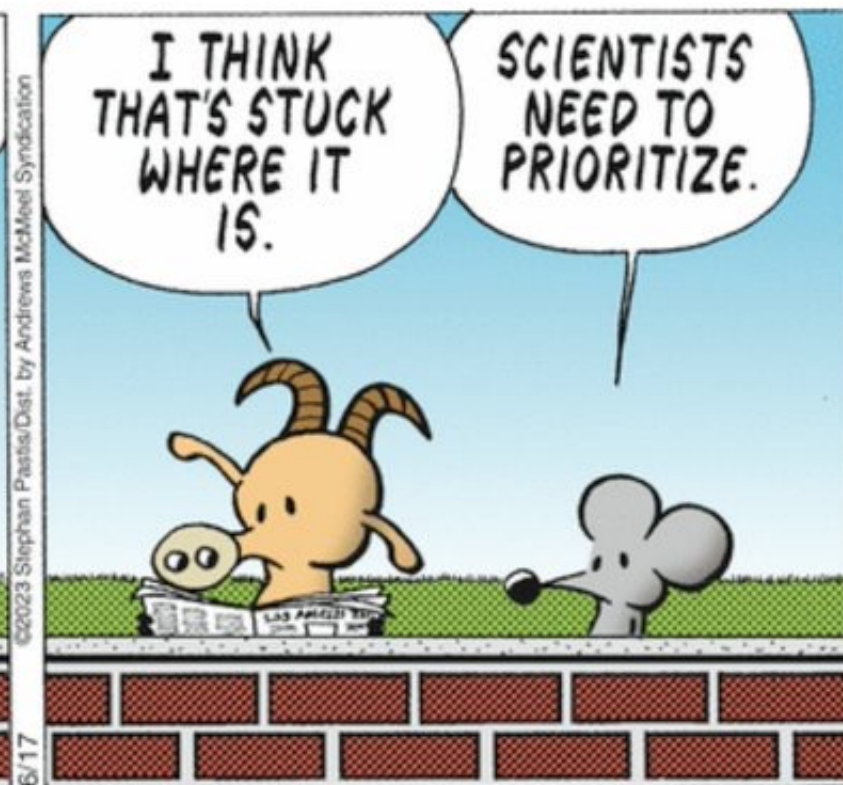
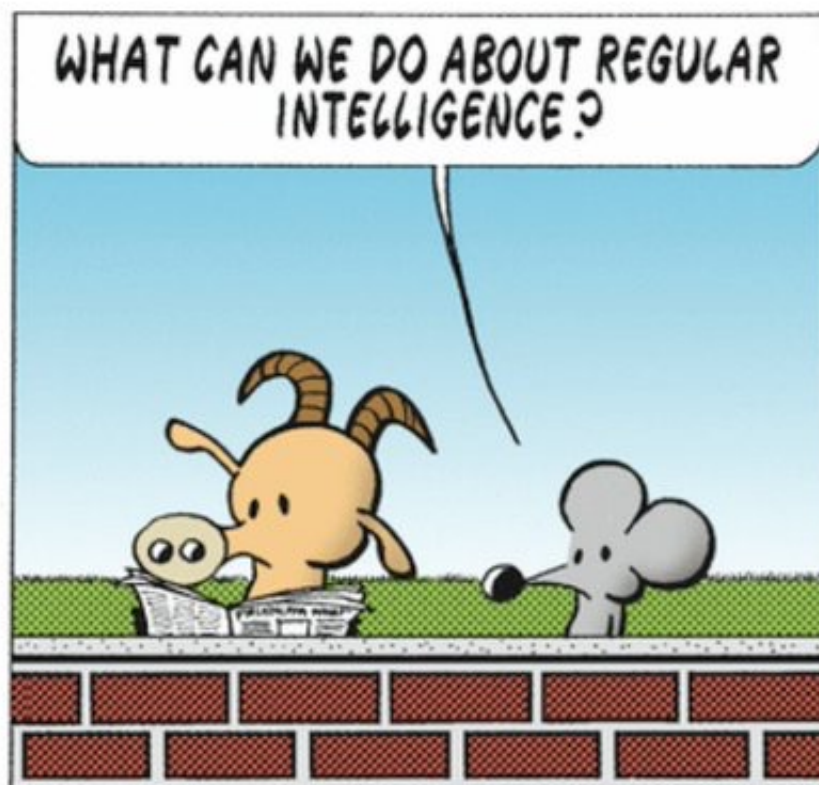
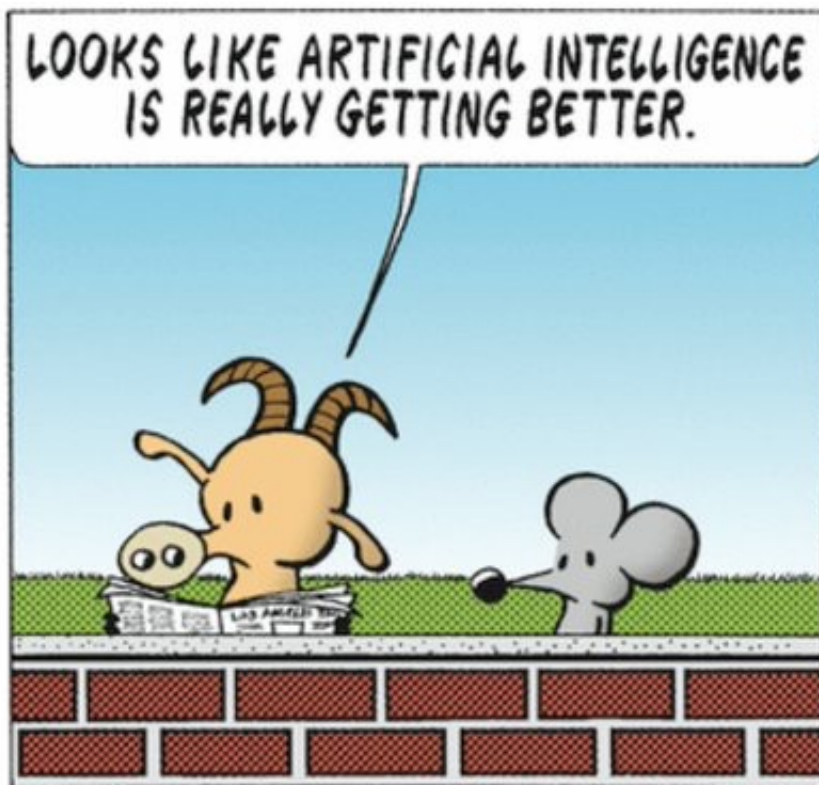


Canva

"Lots of nerd doctors partying at a conference in Ojai California"



Transition to obligatory AI Section



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6/17


Less is More with AI

European Radiology (2023) 33:1629–1640
<https://doi.org/10.1007/s00330-022-09206-3>

COMPUTED TOMOGRAPHY




Is it possible to use low-dose deep learning reconstruction for the detection of liver metastases on CT routinely?

Peijie Lyu^{1,2} • Nana Liu¹ • Brian Harrawood³ • Justin Solomon³ • Huixia Wang¹ • Yan Chen¹ • Francesca Rigioli⁴ • Yuqin Ding^{2,5} • Fides Regina Schwartz² • Hanyu Jiang^{2,6} • Carolyn Lowry⁷ • Luotong Wang⁸ • Ehsan Samei³ • Jianbo Gao¹  • Daniele Marin²

“Radiation dose levels for Deep Learning Image Reconstruction can be reduced 50% while maintaining comparable image quality.”


Lyu P, Liu N, Harrawood B, Solomon J, Wang H, Chen Y, Rigioli F, Ding Y, Schwartz FR, Jiang H, Lowry C, Wang L, Samei E, Gao J, Marin D. Is it possible to use low-dose deep learning reconstruction for the detection of liver metastases on CT routinely? Eur Radiol. 2023 Mar;33(3):1629-1640. doi: 10.1007/s00330-022-09206-3. Epub 2022 Nov 3. PMID: 36323984

Less is More with AI



European Journal of Radiology

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



Feasibility of deep learning k-space-to-image reconstruction for diffusion weighted imaging in patients with breast cancers: Focus on image quality and reduced scan time

Eun Ji Lee^a, Yun-Woo Chang^{a,*}, Jae Kon Sung^b, Benkert Thomas^c

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^b Siemens Healthineers Ltd, Seoul, Korea
^c MR Application Predevelopment, Siemens Healthcare GmbH, Erlangen, Germany

-Deep Learning MRI showed better results than traditional methods in 47% of the time.

Lee EJ, Chang YW, Sung JK, Thomas B. Feasibility of deep learning k-space-to-image reconstruction for diffusion weighted imaging in patients with breast cancers: Focus on image quality and reduced scan time. Eur J Radiol. 2022 Dec;157:110608. doi: 10.1016/j.ejrad.2022.110608. Epub 2022 Nov 13. PMID: 36403564


Less is More with AI

European Radiology (2023) 33:4344–4354
<https://doi.org/10.1007/s00330-022-09298-x>

GASTROINTESTINAL



Low-contrast-dose liver CT using low monoenergetic images with deep learning–based denoising for assessing hepatocellular carcinoma: a randomized controlled noninferiority trial

Jae Seok Bae^{1,2} • Jeong Min Lee^{1,2,3}  • Se Woo Kim⁴ • Sungeun Park⁵ • Seungchul Han⁶ • Jeong Hee Yoon^{1,2} • Ijin Joo^{1,2} • Hyunsook Hong⁷

-Deep Learning contrast CT showed non-inferior image quality with 60% of the contrast.

Bae JS, Lee JM, Kim SW, Park S, Han S, Yoon JH, Joo I, Hong H. Low-contrast-dose liver CT using low monoenergetic images with deep learning-based denoising for assessing hepatocellular carcinoma: a randomized controlled noninferiority trial. *Eur Radiol.* 2023 Jun;33(6):4344-4354. doi: 10.1007/s00330-022-09298-x. Epub 2022 Dec 28. PMID: 36576547

Less is More with AI

Randomized Controlled Trial

> Acta Radiol. 2023 Mar;64(3):1007-1017.

doi: 10.1177/02841851221118476. Epub 2022 Aug 17.

Deep learning reconstruction allows for usage of contrast agent of lower concentration for coronary CTA than filtered back projection and hybrid iterative reconstruction

Chuluunbaatar Otgonbaatar¹, Jae-Kyun Ryu², Jaemin Shin³, Han Myun Kim⁴, Jung Wook Seo⁵, Hackjoon Shim^{2 6}, Dae Hyun Hwang⁴

“application of DLR to the Iohexol-240 significantly improved SNR (signal-to-noise) and CNR (contrast-to-noise); it achieved higher subjective scores compared with hybrid IR at Iohexol-300 (P < 0.001).”

-20% less iodinated contrast

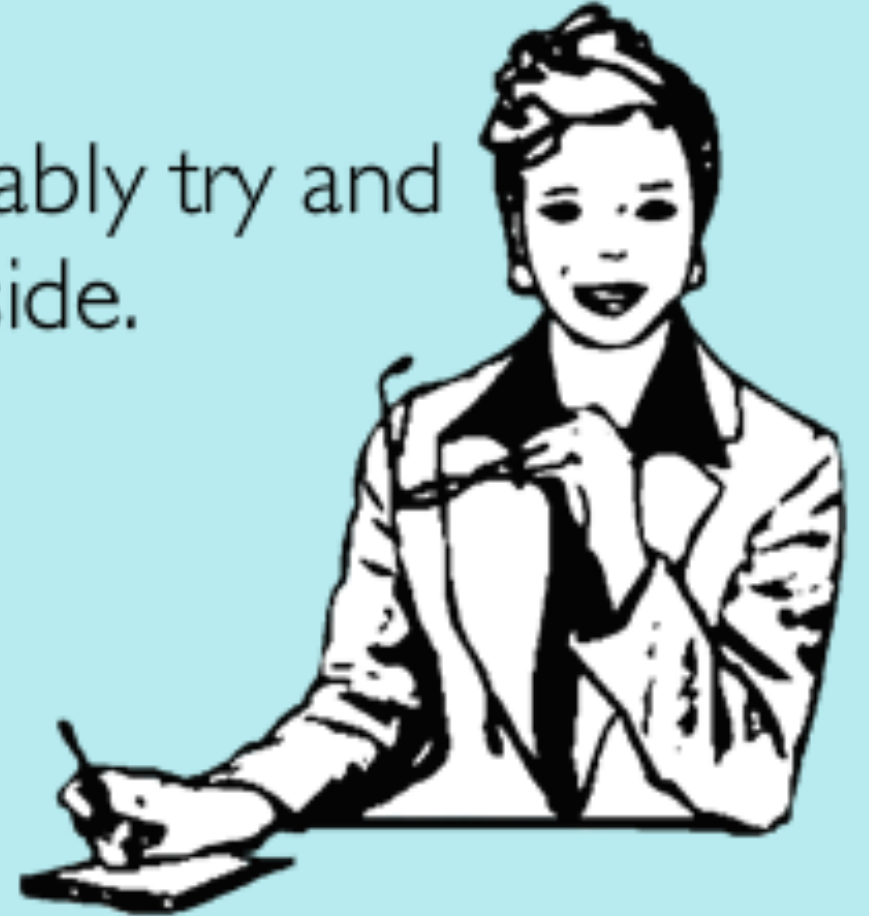
Otgonbaatar C, Ryu JK, Shin J, Kim HM, Seo JW, Shim H, Hwang DH. Deep learning reconstruction allows for usage of contrast agent of lower concentration for coronary CTA than filtered back projection and hybrid iterative reconstruction. Acta Radiol. 2023 Mar;64(3):1007-1017. doi: 10.1177/02841851221118476. Epub 2022 Aug 17. PMID: 35979586.



*Transition – Colin
and the home stretch*

Oh I'm in health informatics.

You should probably try and
get on my good side.



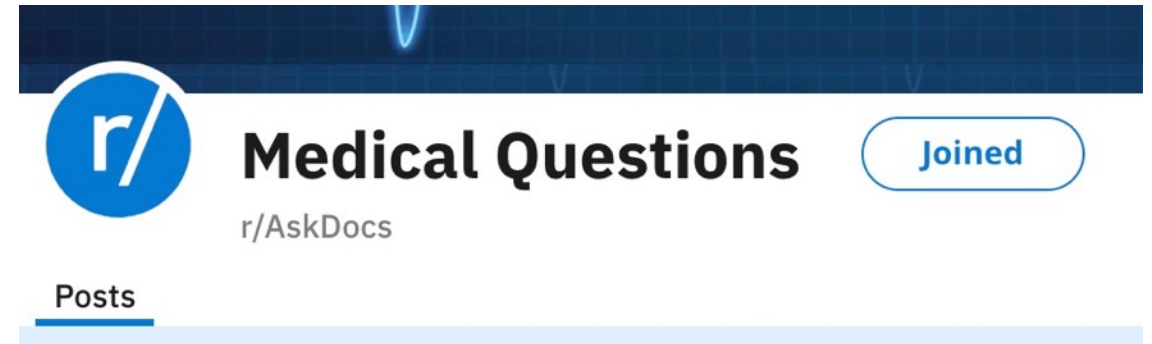
somee cards
user card



Comparing Physician and Artificial Intelligence Chatbot Responses to Patient Questions Posted to a Public Social Media Forum

John W. Ayers, PhD, MA^{1,2}; Adam Poliak, PhD³; Mark Dredze, PhD⁴; et al

- The ultimate Reddit exercise!
- ~200 real questions and exchanges from October 2022
- Put the patient questions into ChatGPT and then posted the same question along with real doctor answers and then ChatBot answers in Nov 2023
- Healthcare team then judged "which was better"





Question about needing to see a physician following injury that occurred by hitting head on a metal bar while running, resulting in lump on head, headache, and sore neck.

Things that signify you should see a doctor:

- Nausea/vomiting
- Dizziness
- Severe or worsening headache
- Loss of consciousness
- Confusion
- Neck stiffness
- Problems with vision
- Limb weakness

If you develop any of these in the next 24 h, rush to the emergency room.

It's always best to err on the side of caution when it comes to head injuries. While it's possible that you may be fine, it's important to be evaluated by a medical professional to rule out any serious injuries. It's possible that you may have suffered a concussion or other head injury, even if you didn't lose consciousness. Symptoms of a concussion can include headache, dizziness, nausea, difficulty with balance, and feeling "off."

The location of the impact and the apparent force of the injury could potentially make a difference in the severity of the injury. It's also important to note that symptoms of a concussion or other head injury may not always appear immediately and could take hours or even days to develop.

It's important to seek medical attention as soon as possible if you experience any of the following symptoms after a head injury:

- Loss of consciousness, even if it's just for a few seconds
- Severe or worsening headache
- Nausea or vomiting
- Slurred speech
- Difficulty with balance or coordination
- Seizures
- Changes in behavior or personality
- Clear fluid draining from the nose or ears

It's also a good idea to see a doctor if you experience neck pain after a head injury, as this could be a sign of a neck injury.

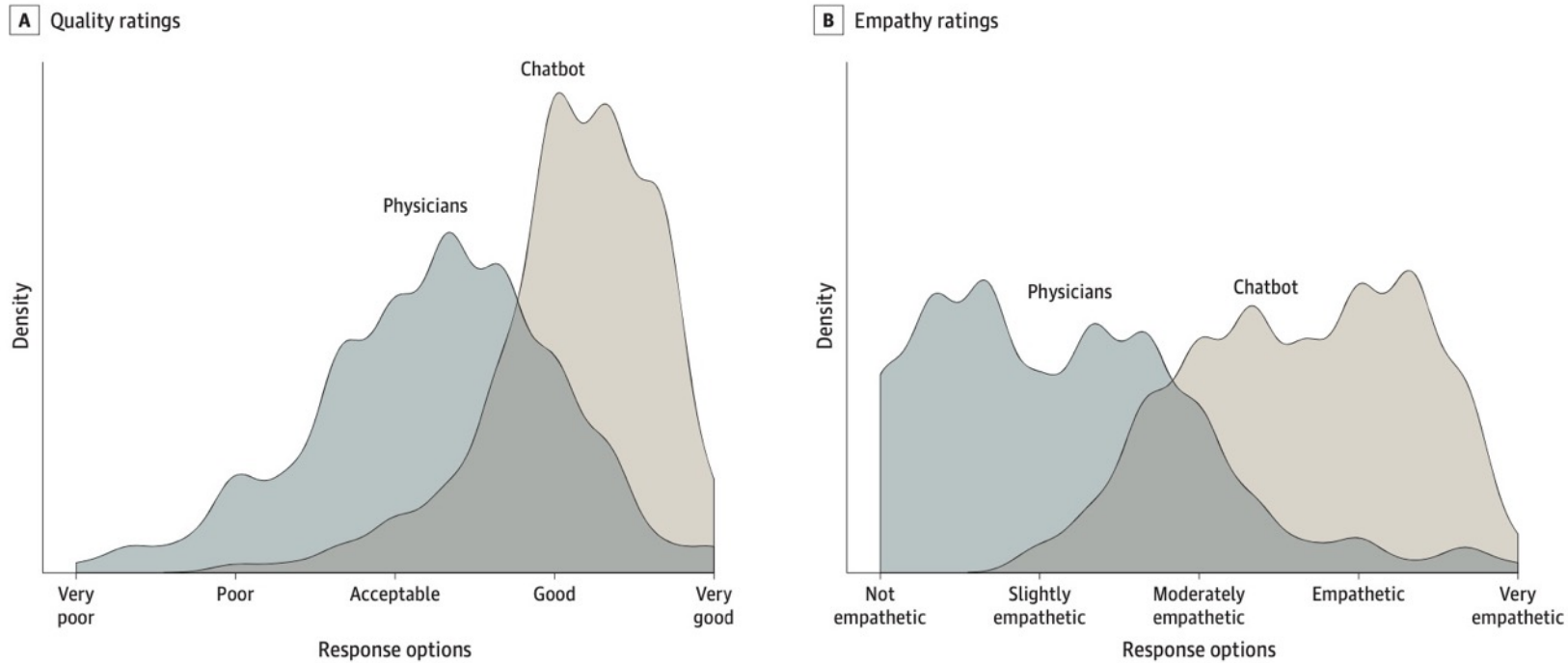
In the meantime, try to rest and avoid activities that could potentially cause further injury to your head, such as contact sports or activities that involve high speeds or heights. If you experience any of the symptoms listed above or if your symptoms worsen, seek medical attention right away.

- 100% preferred the chatbot
- 4.33 mean quality score (chatbot)
- 4.67 mean quality score (physician)
- 4.67 mean empathy score (chatbot)
- 2.33 mean empathy score (physician)



“ChatGPT doesn’t get tired.....”

Figure. Distribution of Average Quality and Empathy Ratings for Chatbot and Physician Responses to Patient Questions



AI has better ‘bedside manner’ than some doctors, study finds

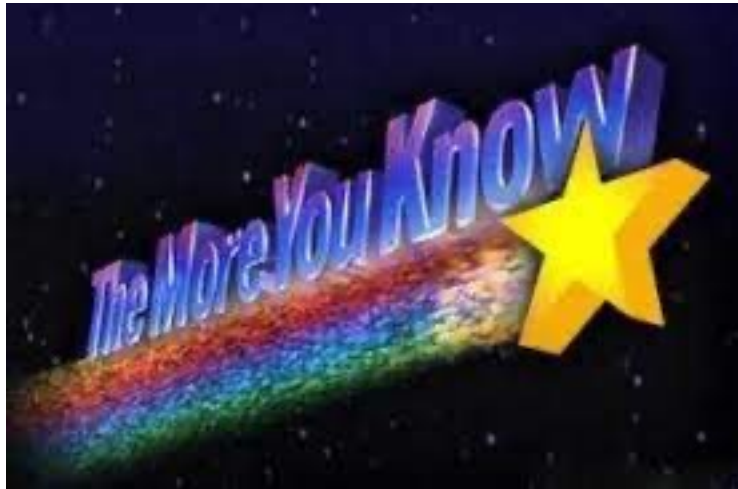
ChatGPT rated higher in quality and empathy of written advice, raising possibility of medical assistance role

Kernel density plots are shown for the average across 3 independent licensed health care professional evaluators using principles of crowd evaluation. A, The overall quality metric is shown. B, The overall empathy metric is shown.



Electronic Health Record Legal Settlements in the US Since the 2009 Health Information Technology for Economic and Clinical Health Act

Nate C. Apathy, PhD; Jessica L. Howe, MS; Seth A. Krevat, MD; Aaron Zachary Hettinger, MD, MS; David W. Bates, MD; David C. Classen, MD, MS; Raj M. Ratwani, PhD



- 6 vendors
- ~\$400M in settlements
- Kickbacks to clinicians
- Capability misrepresentation (MU 1 and 2)

Table. US Department of Justice Settlements With EHR Vendors

EHR vendor	Settlement		Description of allegations	No. of clinicians attesting to meaningful use of an EHR product during the alleged period of misconduct
	Year	Amount in millions, \$		
eClinicalWorks ^a	2017	155	<ul style="list-style-type: none">• Misrepresented EHR capabilities to certify a product (eg, hardcoding only the required drug orders for certification test)• Paid kickbacks to certain customers for product promotion	35 451
Greenway Health LLC ^b	2019	57.25	<ul style="list-style-type: none">• Misrepresented EHR capabilities to certify a product (eg, hardcoding clinical vocabulary used in certification test)• Paid kickbacks for product promotion• Miscalculated interoperability measures reported to obtain meaningful use incentive payments	12 194
Practice Fusion Inc ^c	2020	145	<ul style="list-style-type: none">• Misrepresented EHR capabilities to certify a product (eg, EHR was unable to create standardized patient information export summaries)• Solicited and received kickbacks from an opioid company in exchange for using the product to influence physician prescribing of opioids	6230
Viztek LLC ^d	2020	0.5	<ul style="list-style-type: none">• Misrepresented EHR capabilities to certify a product (eg, hardcoding software to pass certification testing)	39
athenahealth Inc ^e	2021	18.25	<ul style="list-style-type: none">• Paid unlawful kickbacks to generate sales of EHR products	22 526
CareCloud Health Inc ^f	2021	3.8	<ul style="list-style-type: none">• Paid unlawful kickbacks to generate sales of EHR products	391

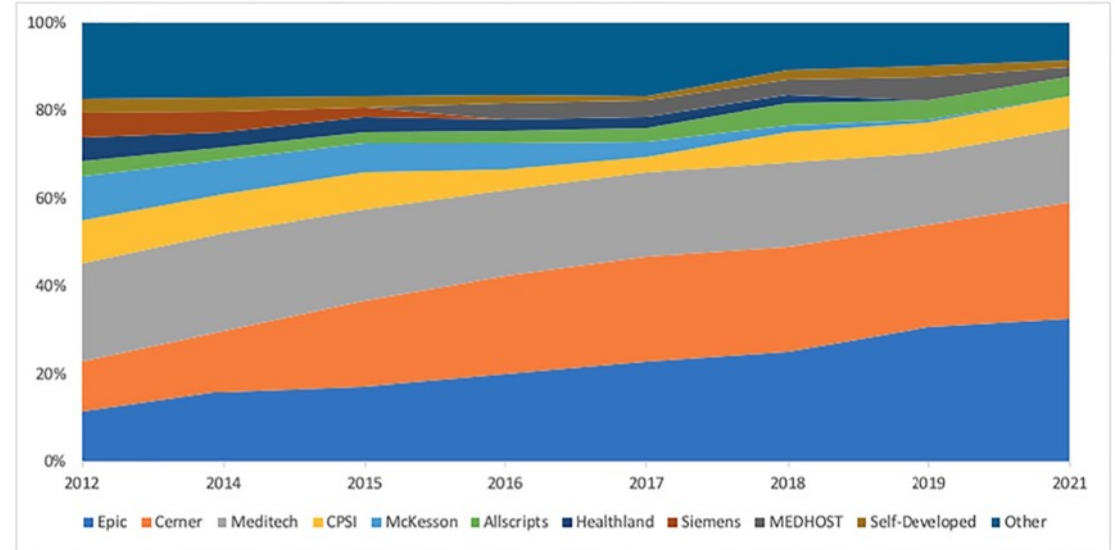


Trends in US Hospital Electronic Health Record Vendor Market Concentration, 2012–2021

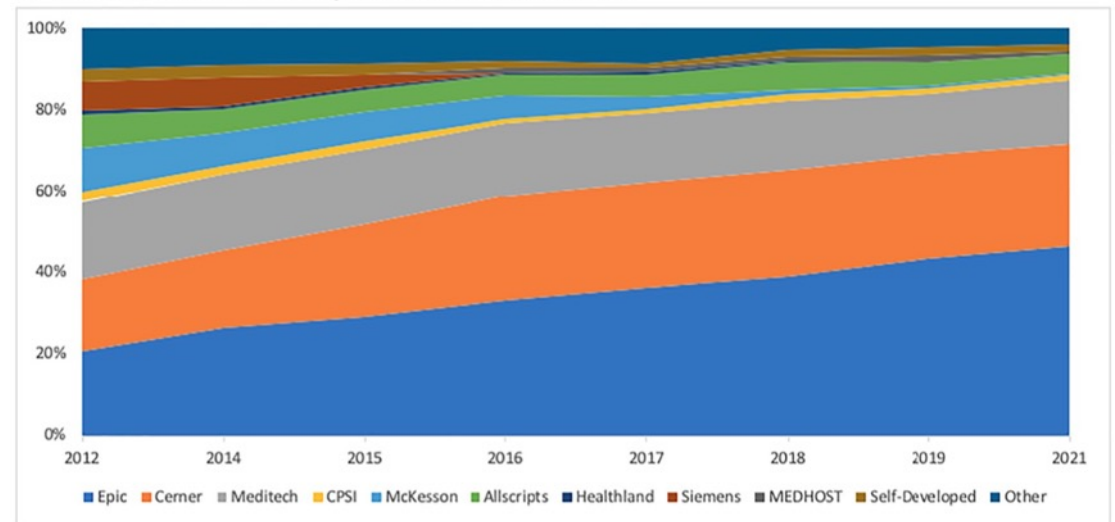


- Just a nice observational paper confirming what we were already perceiving in the market
- Cerner / Epic = 71% of beds now (2021)
- We've moved from a competitive market to "highly concentrated"

a EHR Vendor Market Share by Number of Hospitals, 2012-2021



b EHR Vendor Market Share by Number of Beds, 2012-2021





Original Investigation | Emergency Medicine

Ransomware Attack Associated With Disruptions at Adjacent Emergency Departments in the US

Christian Dameff, MD, MS; Jeffrey Tully, MD; Theodore C. Chan, MD; Edward M. Castillo, PhD, MPH; Stefan Savage, PhD; Patricia Maysent, MHA, MBA; Thomas M. Hemmen, MD, PhD; Brian J. Clay, MD; Christopher A. Longhurst, MD, MS

- Studies the impact of Health IT downtime due to ransomware on an adjacent health system (UCSD)
- Scripps attack May 2021 – lasted 4 weeks
- Looks at the ED metrics pre / during / post attack
 - LOS / Elope / Admissions / etc
 - Overall Diversion Hours
 - Stroke Quality Measures



JAMA
Network | Open™



Figure 1. Emergency Department (ED) Census, Admissions, and Incomplete Care Per Day

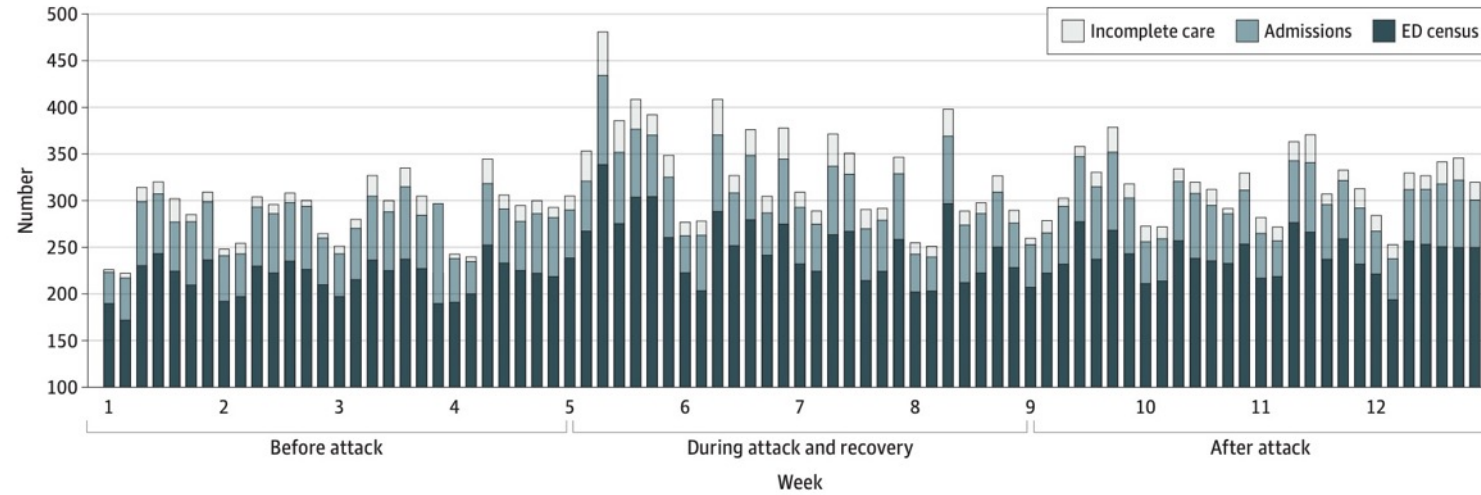


Table 3. Stroke Census and Performance Metrics

Characteristic	No.			P value			
	Before attack	During attack and recovery	After attack	Overall	Before attack vs attack	Attack vs after attack	Before vs after attack
ED stroke codes	59	103	65	.009	.01	.01	.98
Confirmed strokes	22	47	28	.02	.02	.047	.60
Acute treatment							
tPA	5	9	1	No statistical analysis performed ^a			
EVT	2	7	3	No statistical analysis performed ^a			
Total	7	16	4	No statistical analysis performed ^a			
Door-to-CT scan time, median (IQR), min	19 (11-33)	18 (9-34)	20 (10-32)	.69	No further statistical analysis performed ^b		
Door-to-tPA administration time, median (IQR), min	35 (31-87)	33 (27-44)	29 ^a	No statistical analysis performed ^a			
Door-to-EVT groin puncture, median (IQR), min	85 ^a	79 (59-106)	84 (81-86)	No statistical analysis performed ^a			



Worth the read - Appendix

Case report

Clinical decision support malfunctions related to medication routes: a case series

Adam Wright¹, Scott Nelson ¹, David Rubins^{2,3,4}, Richard Schreiber ⁵, and Dean F. Sittig ⁶

Perspective

Do electronic health record systems “dumb down” clinicians?

Genevieve B. Melton ^{1,2,3}, James J. Cimino ^{4,5,6}, Christoph U. Lehman ^{7,8,9,10}, Patricia R. Sengstack^{11,12}, Joshua C. Smith¹³, William M. Tierney^{14,15}, and Randolph A. Miller¹³



AI IN MEDICINE

Benefits, Limits, and Risks of GPT-4 as an AI Chatbot for Medicine

Peter Lee, Ph.D., Sebastien Bubeck, Ph.D., and Joseph Petro, M.S., M.Eng.

Using AI-generated suggestions from ChatGPT to optimize clinical decision support

Siru Liu¹, Aileen P. Wright^{1,2}, Barron L. Patterson³, Jonathan P. Wanderer^{1,4},
Robert W. Turer ^{5,6}, Scott D. Nelson ¹, Allison B. McCoy ¹, Dean F. Sittig ⁷, and
Adam Wright ¹



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Informatics in Medicine Unlocked

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

What unique knowledge and experiences do healthcare professionals have working in clinical informatics?

Sophie Brouat^{a,b,c}, Clare Tolley^{b,d}, David W. Bates^{e,f,g}, James Jenson^b, Sarah P. Slight^{b,d,e,*}

^a East and North Hertfordshire NHS Trust, Hertfordshire, UK

^b School of Pharmacy, King George VI Building, Newcastle University, Newcastle, UK

^c School of Medicine, Pharmacy and Health, Durham University, Durham, UK

^d Newcastle Upon Tyne Hospitals NHS Foundation Trust, Newcastle, UK

^e The Centre for Patient Safety Research and Practice, Division of General Internal Medicine and Primary Care, Brigham and Women's Hospital, Boston, MA, USA

^f Harvard Medical School, Boston, MA, USA

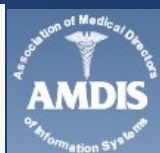
^g Harvard School of Public Health, Boston, MA, USA



Wanna be a radiologist?

https://huggingface.co/spaces/StanfordAIMI/radiology_report_generation

The screenshot shows a web browser window displaying a Hugging Face Space. The browser's address bar shows the URL `https://huggingface.co/spaces/StanfordAIMI/radiology_report_generation`. The page title is "Automatic Radiology Report Generation". Below the title, there is a description: "This demo gives you possibility to select a chest x-ray and ask a trained A.I. to automatically generate the radiology report. Feel free to play with the parameters, or to f words in the generation!". Below the description, it says "Trained with ViLMedic by JB (jbdel@stanford.edu)". The main content area is divided into two sections: "Image to run" and "output 0". The "Image to run" section contains the text "Drop Image Here - or - Click to Upload". The "output 0" section contains a code editor with a cursor and a pair of curly braces `{..}`.



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