Update in Clinical Informatics

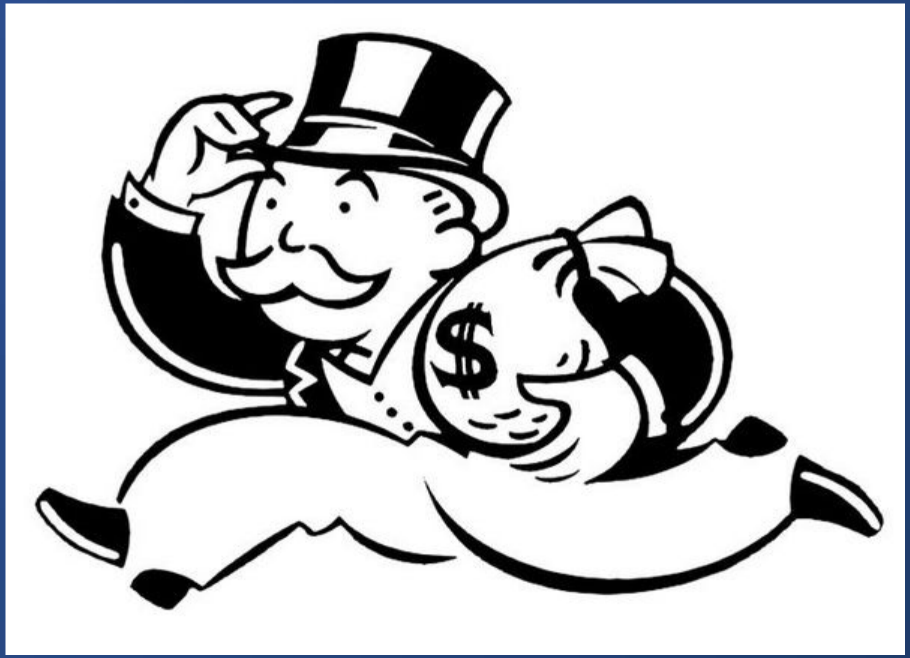
(Sorry, us again. No one else would do it)

AMDIS PCC
Ojai, California
June 2022

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

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

Conflicts



Dr. “Daddy Warbuck’s” Banas
-DrFirst

-zilch

Review Methodology

Hmmm. I used to be a CMIO, now I am on the dark side. I am ***supposed*** to be on top of the literature and opinions. What cool things did I read last year?

I am part time, lost my grants. Bored, will over analyze with unnecessarily complex methodology.

Bill's Review Methodology

Search #1) 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..)

Selected 38 MESH topics. Compared to last years query and added 5 for a total of 43 MESH topics

Humans, from 2021/6/1→2022/5/31 → **36.911**

Search #2) Select informatics MESH headings; “Artificial Intelligence“, "data“, "geographic information systems“, "informatics“, "information“, "machine learning“, "personnel staffing and scheduling information systems“

AND all MESH with **"clinical", "medical", "nursing", "dental", "health“.**

Humans, from 2021/6/1→2022/5/31 → **27,223**

Search #1 OR #2 → **46,422**

Did not require English Language (>98%) or an abstract for quantitative analysis

Bill’s Review Methodology (2)

Analysis

A) Look at trends over time, funding, study design, COVID-19, etc..

B) Very simple word and phrase counting of English titles and abstracts in cohort of 46,422

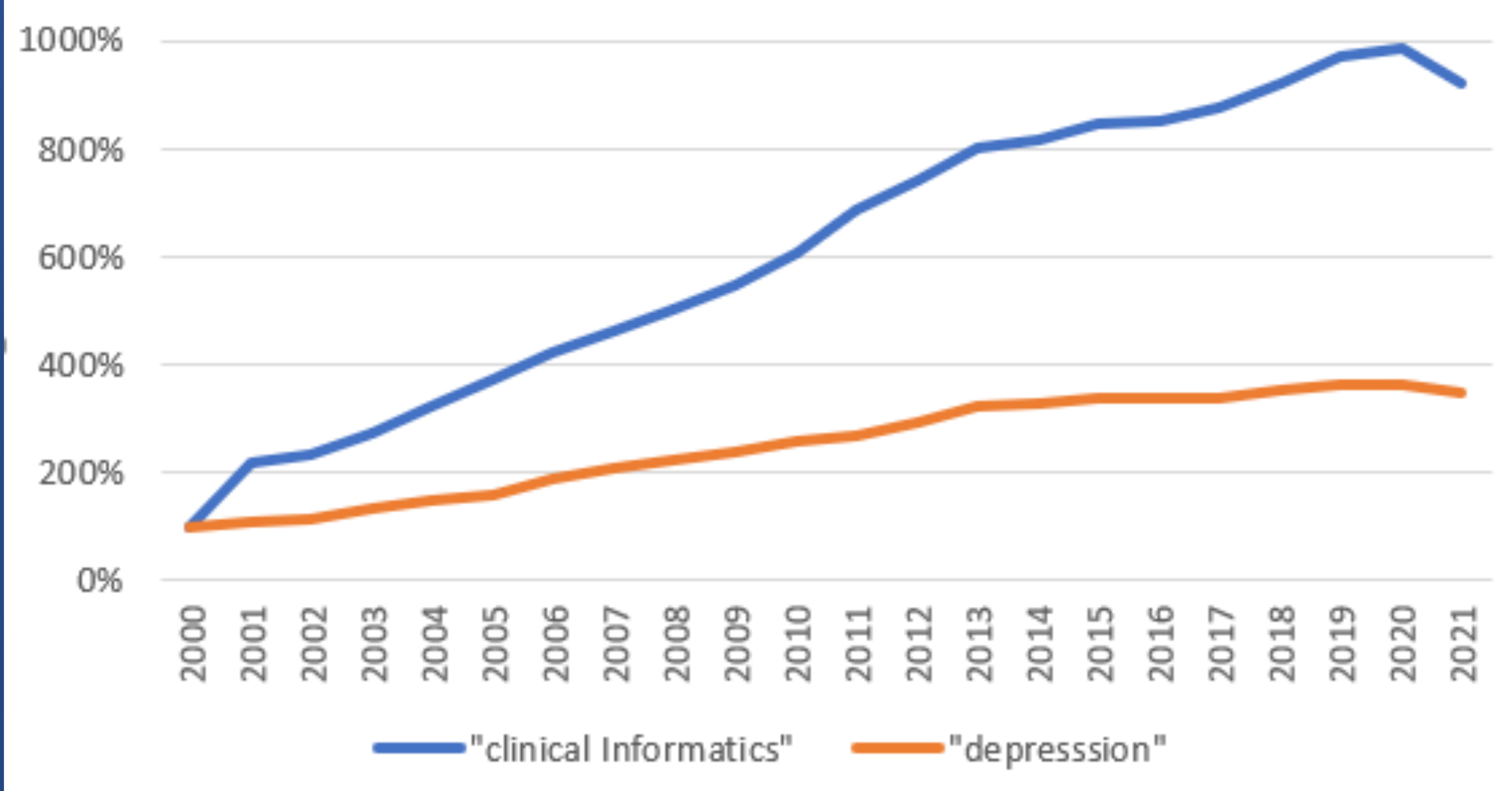
C) Select and review some papers from the cohort of clinical trials, with a bias toward self-promotion and RCt’s, N=1215

D) Let Dr. Banas mix in his publications, twitters, Instagram's, Facebook blurbs, Redditt's, random thoughts, daily affirmations, snippets from MSNBC & FOX etc…, as well as his legendary sense of humor.

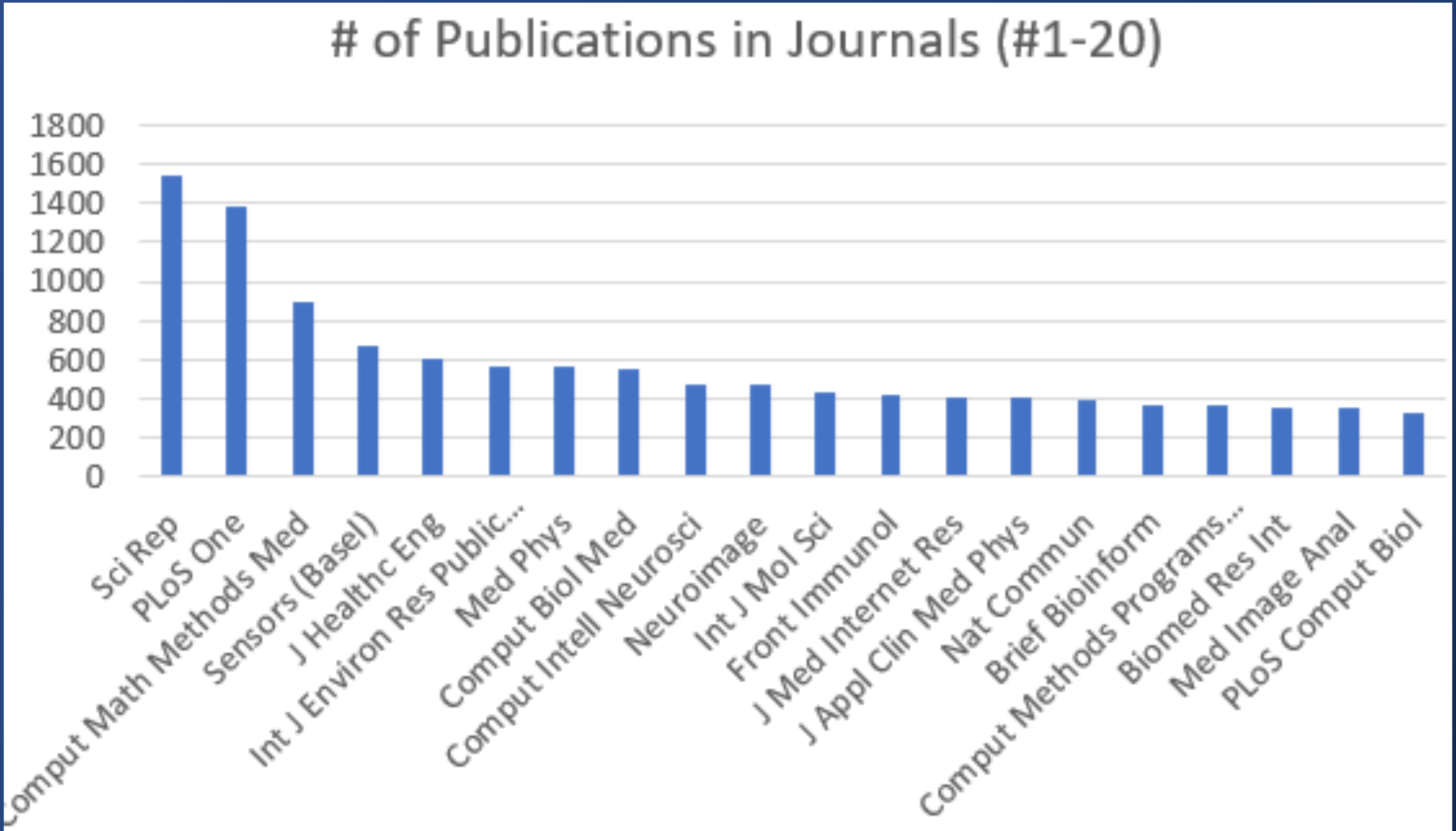
Cook at 425 for 60 minutes

Growth in Publications

(compared to 2000, using depression/anxiety/bipolar as comparator)



What Journals?



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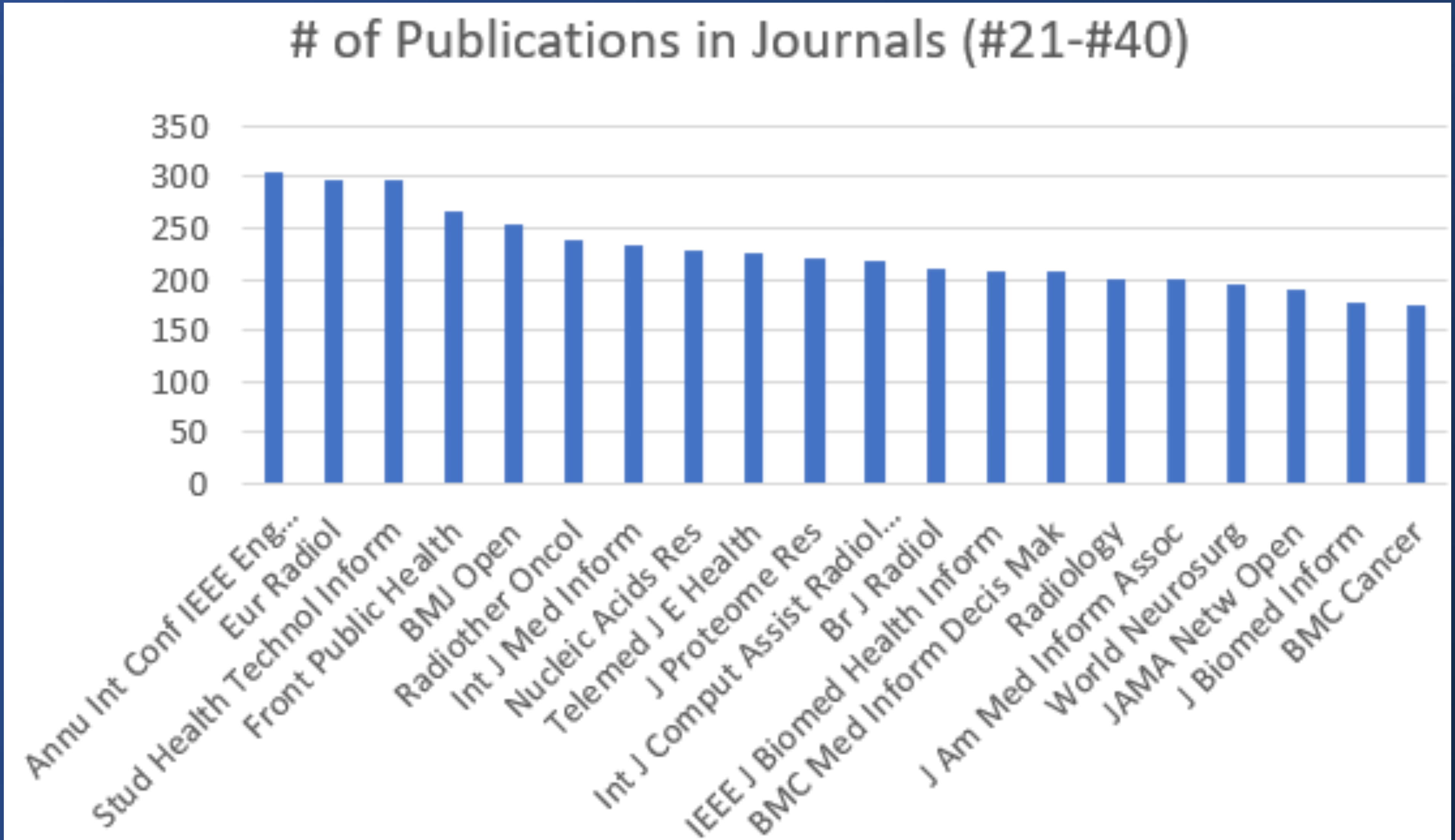
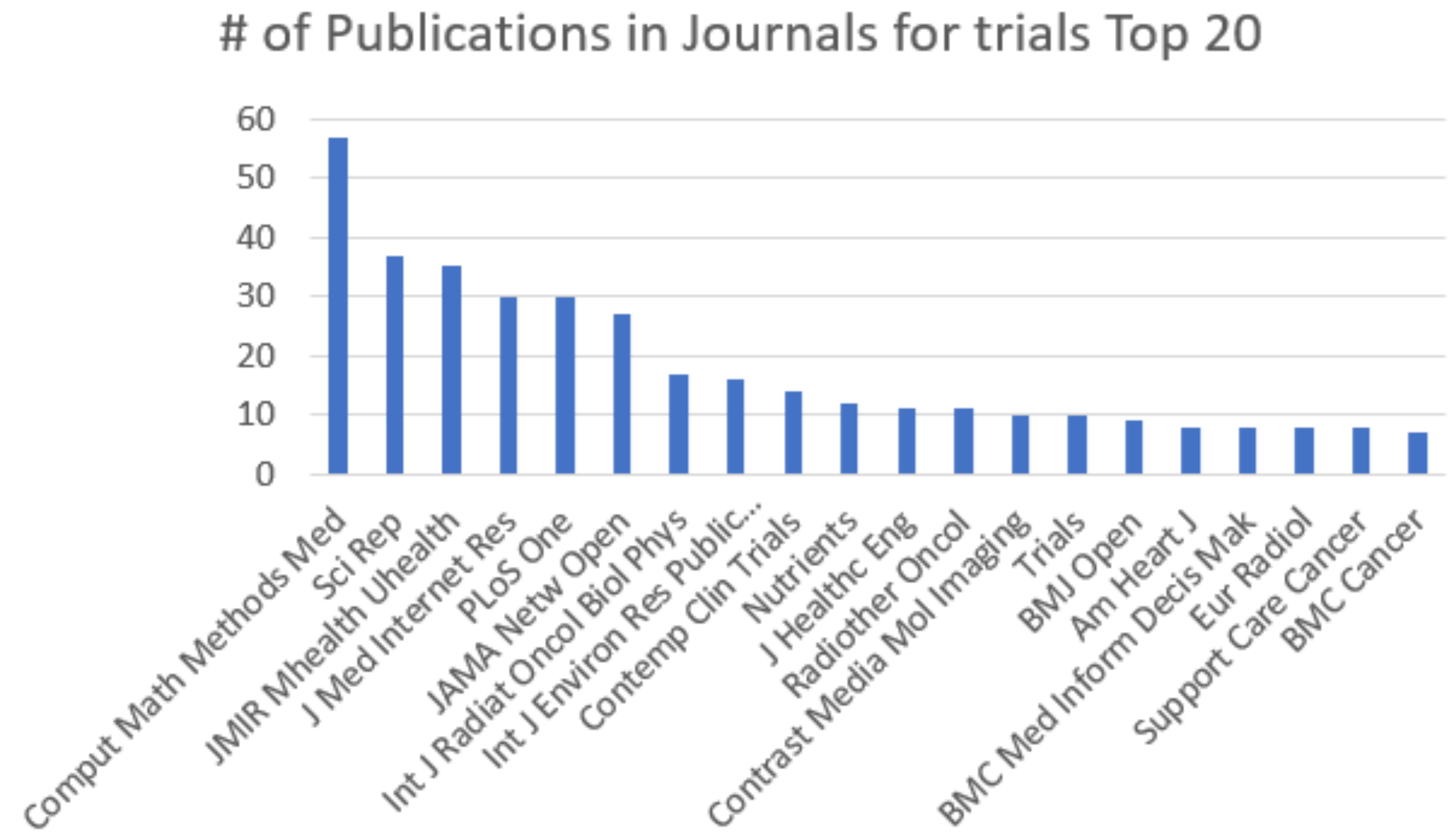
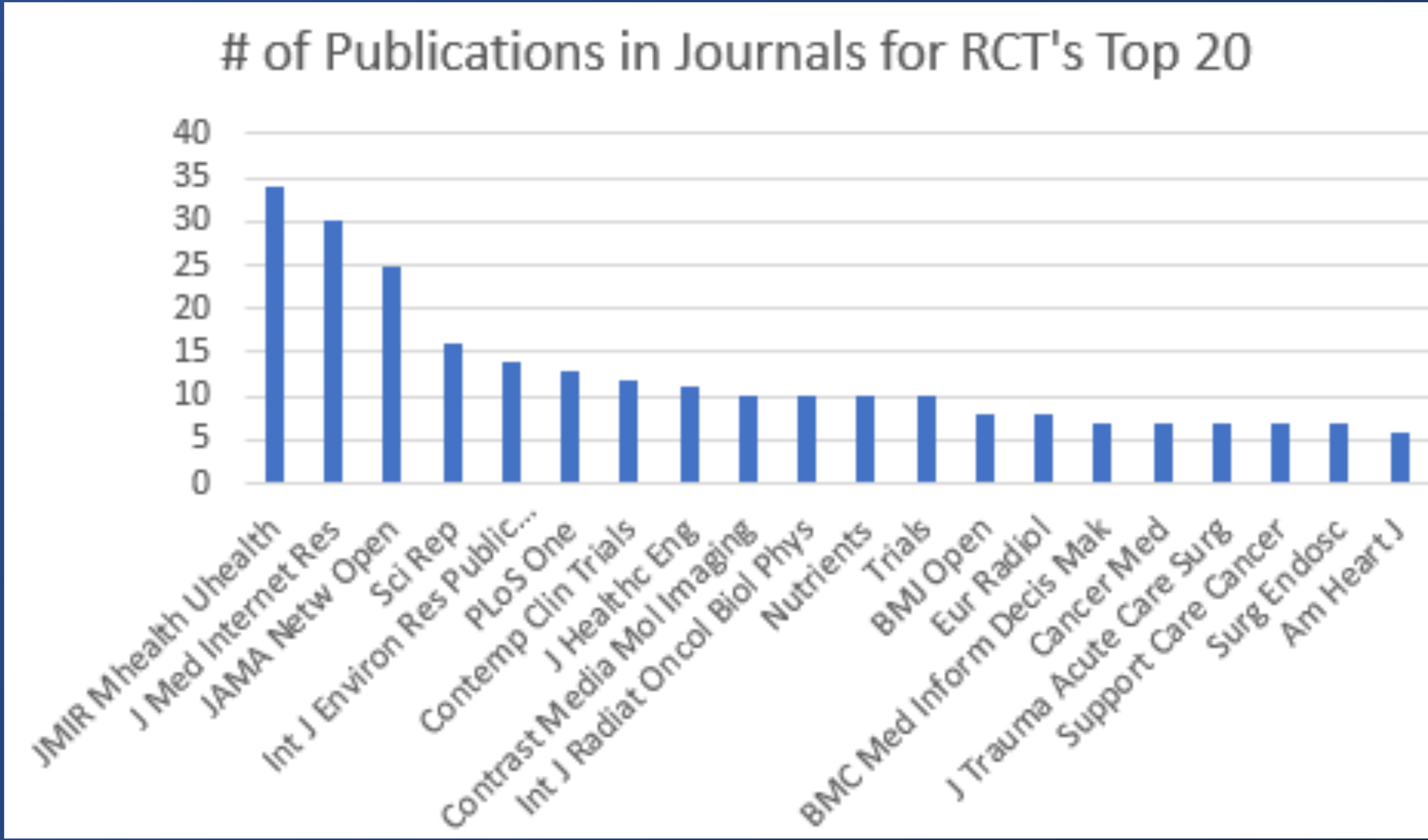


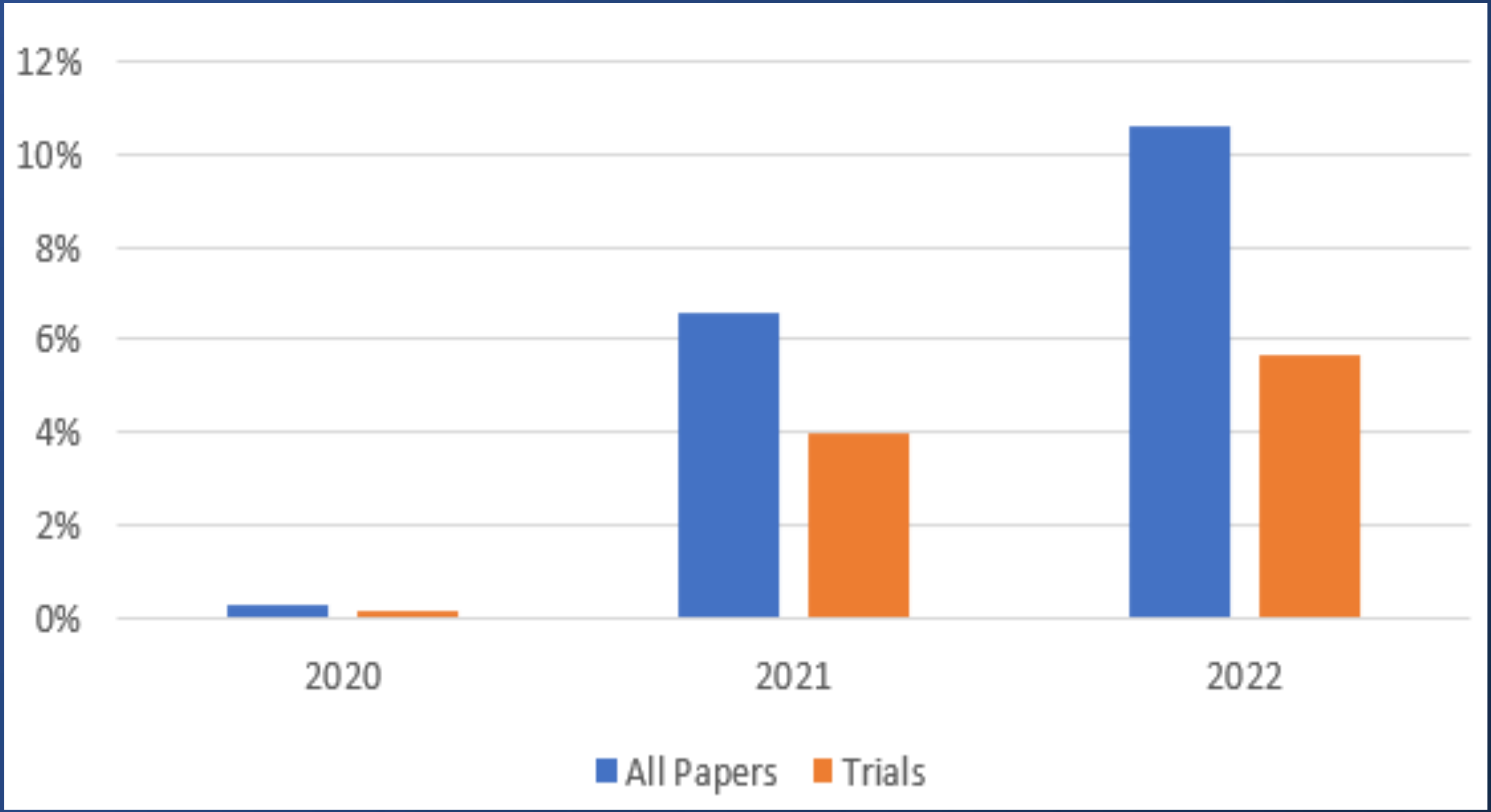
What Journals are the trials published in ?



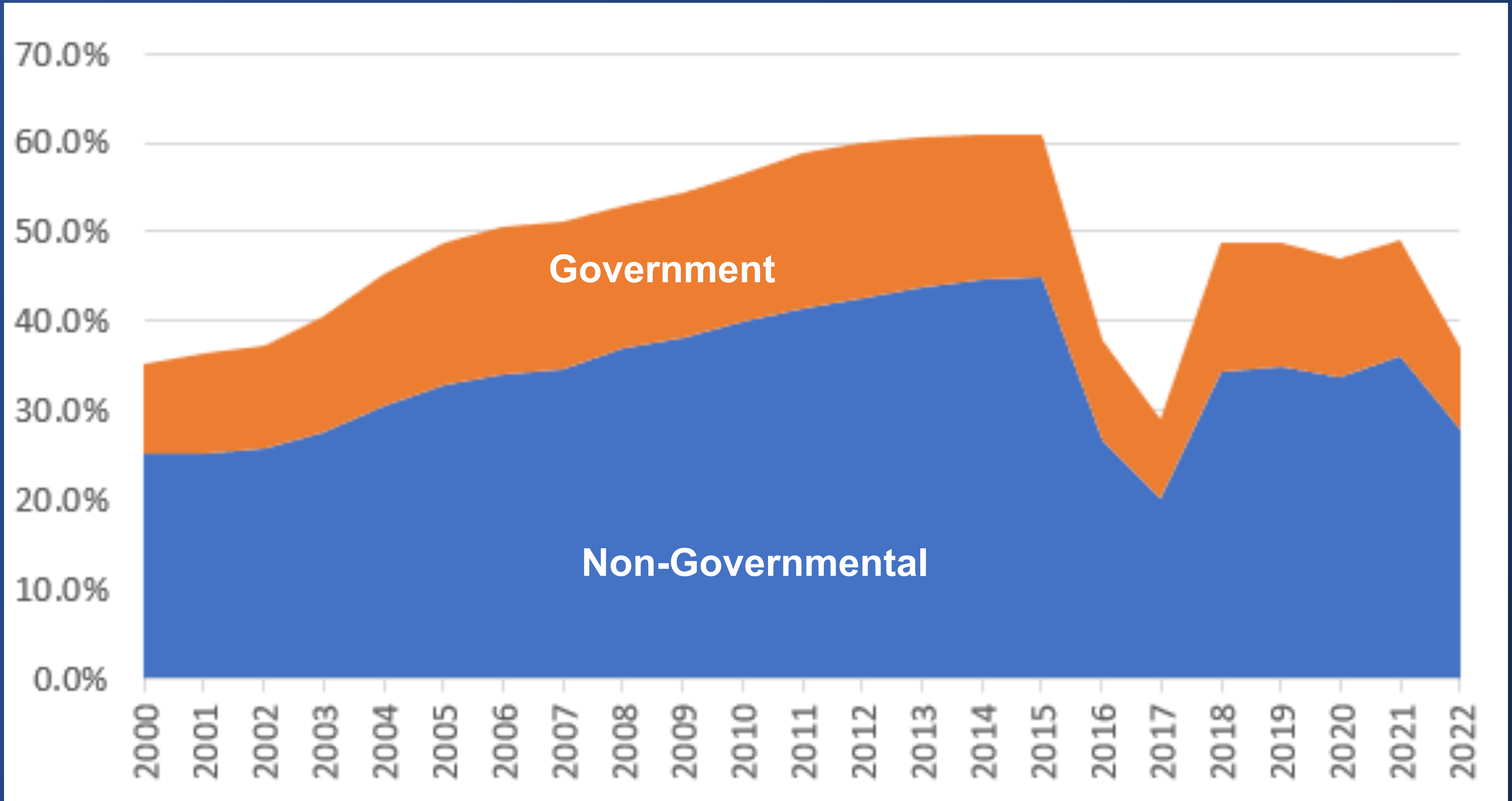
What Journals are the RCTs published in ?



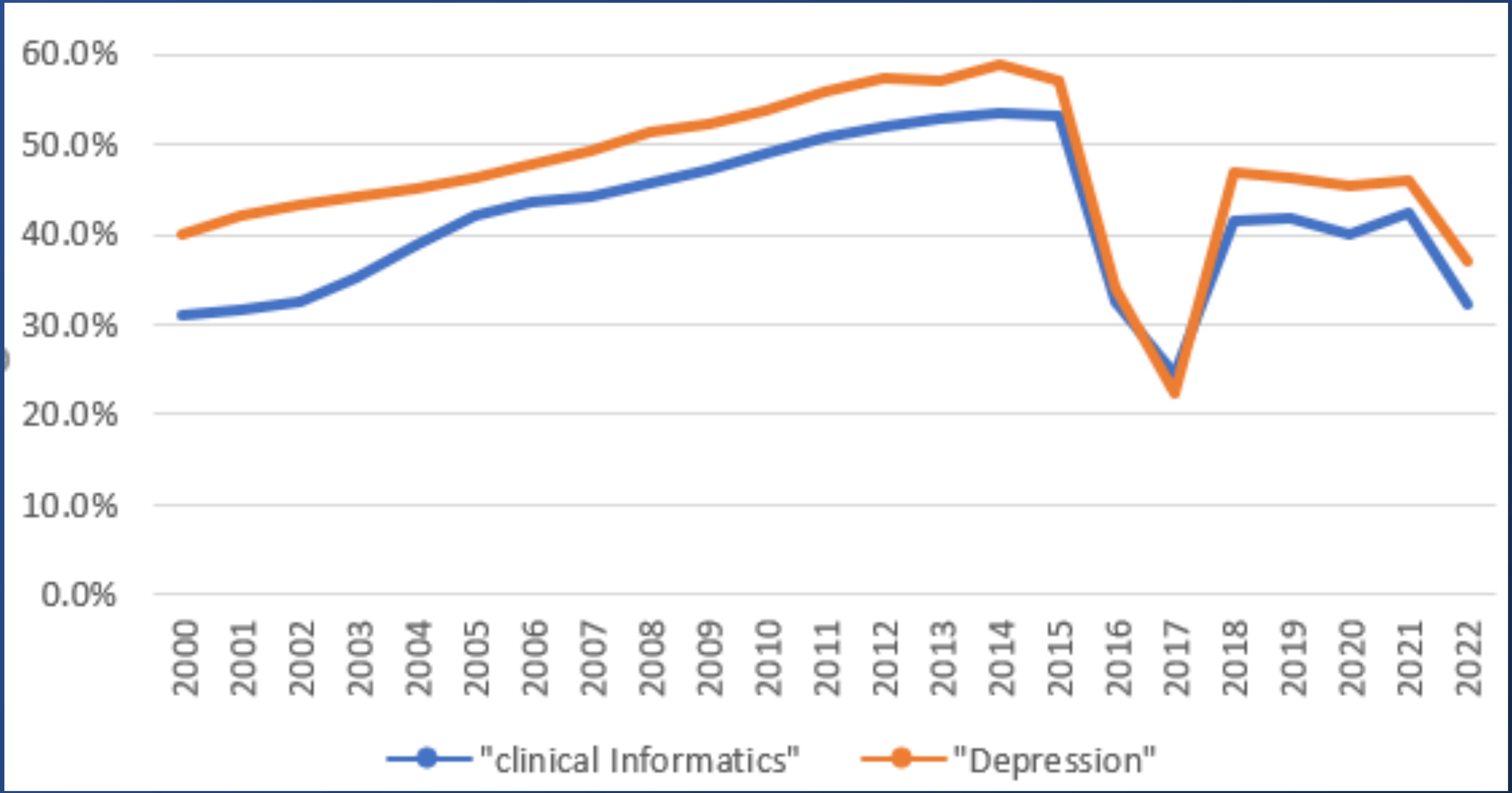
Proportion of publications related to COVID-19



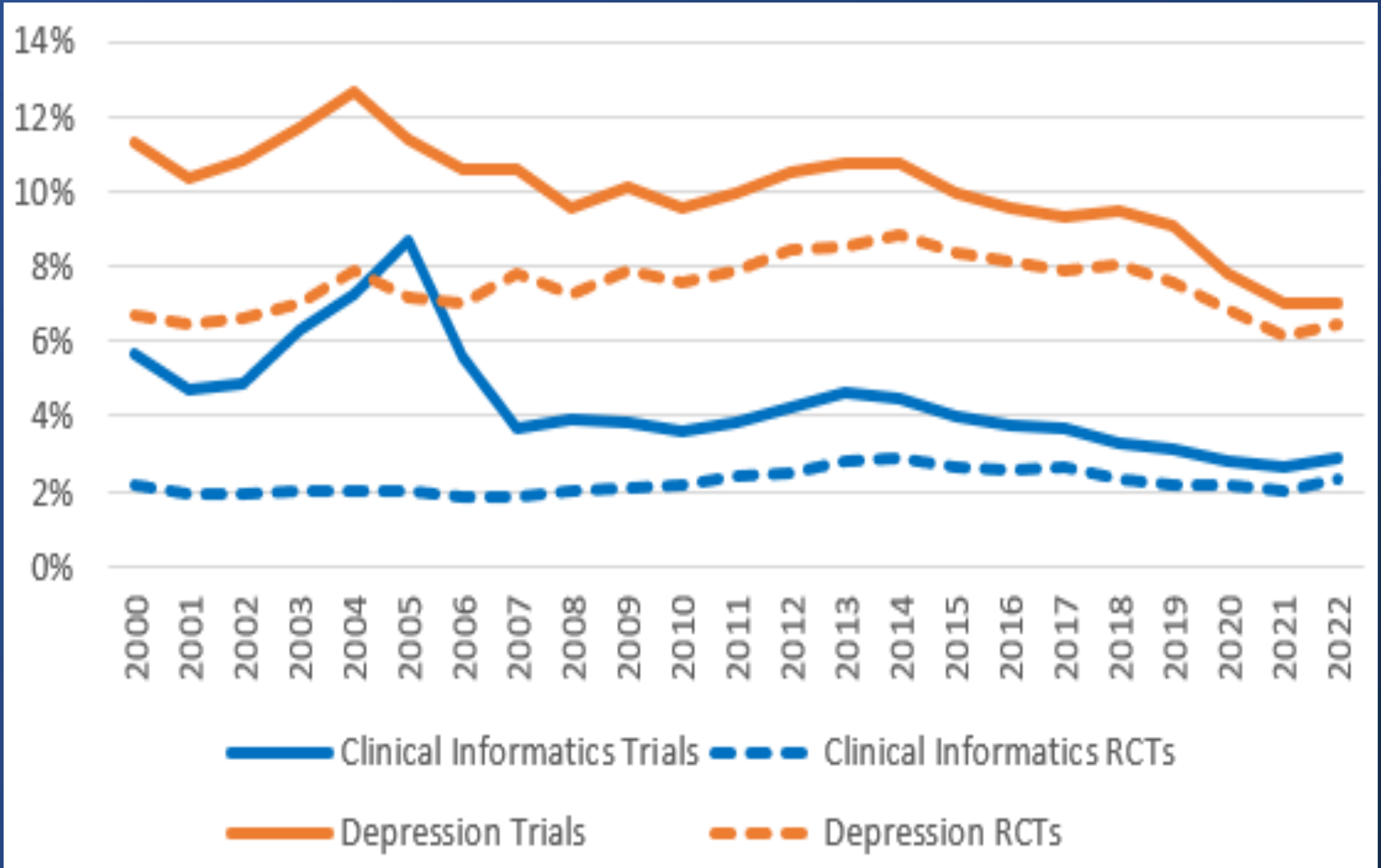
% of publications with funding



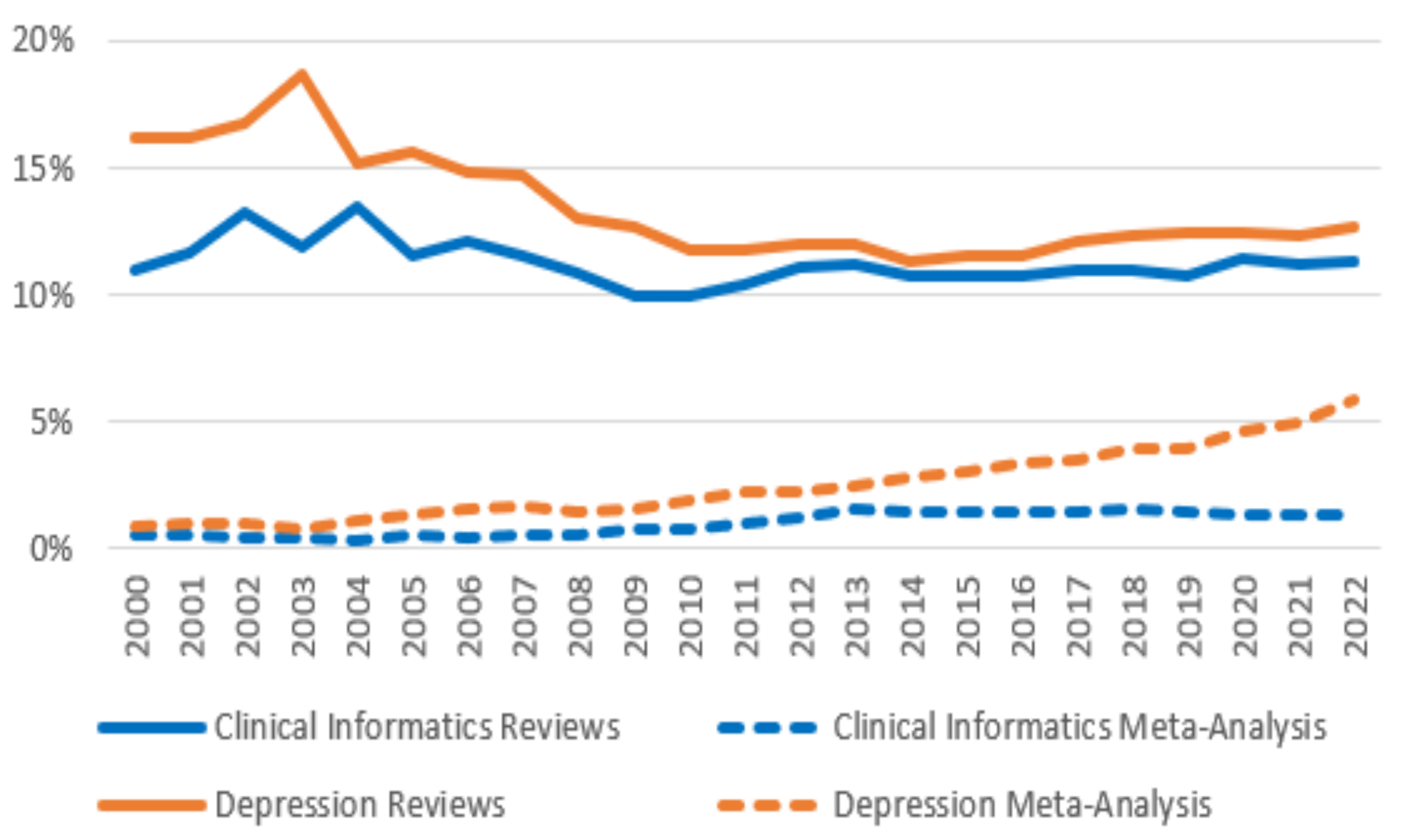
% of publications with any funding



Proportion of publications that are trials or RCTs

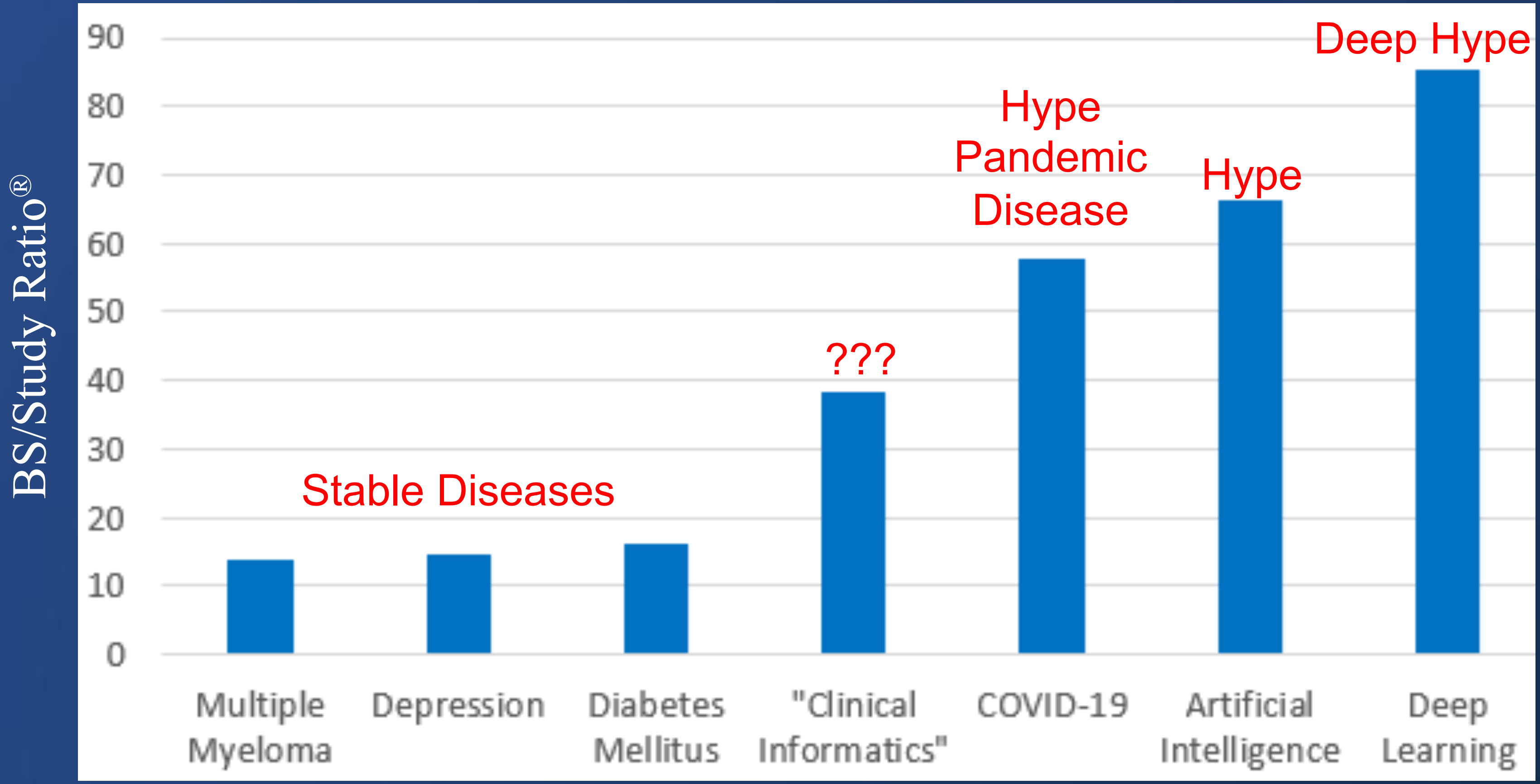


Proportion of Publications that are Reviews or Meta-Analyses



BS/Study Ratio®

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



Repeated themes in the trial Corpus

things that have gone down

- -automated reminders
- -games/gamification
- -texts
- -CDS
- -portals
- -e-mail
- -robots

tele du jour

- -teleCare
- -teleDermoscopy
- -teleMedicine
- -telePresence
- -teleUltrasound
- -teleClinicalCare
- -teleHealth
- -teleMonitoring
- -telePyschiatry
- -teleConsultation
- -teleIntegrated
- -telePhysiatry
- -teleRehab

CDS

- -antenatal care
- -dangerous prescriptions
- -cancer prevention
- -prediabetes
- -psychotherapy
- -atrial fibrillation
- -heart disease prevention
- -HIV med compliance
- -pain management
- -vaccination
- -clinical documentation
- -imaging in ED
- -hypercholesteremia
- -polypharmacy

Repeated themes in the trial Corpus (cont.)

AI, machine learning, deep learning, deeper learning, deepest learning

- -alopecia (hair counting)
- -colonoscopy for Cancer
- -IBD
- -retinal Analysis
- -prognosis s/p surgery
- -traumatic brain injury
- -ARDS
- -erroneous prescriptions
- -imaging for cancer
- -malignant pathology
- -suicidal Ideation
- -COVID
- -fertility
- -imaging
- -myocardial Infarction
- -radiation therapy

mHealth

- -cannabis use
- -contraceptive use
- -exercise
- -low back pain
- -motor skills
- -pelvic floor exercise
- -sleep
- -cardiovascular Risk
- -DM type I
- -HIV prevention
- -medication adherence
- -nutrition
- -perioperative
- -stress or PTSD
- -cigarette smoking
- -DM type II
- -hyperphosphatemia
- -medication levels
- -pediatric hosp safety
- -screening
- -weight loss

"omics"

- -dosiomics
- -integrative omics
- -metagenomics
- -radiomics
- -economics
- -lipidomics
- -multi-Omics
- -transcriptomics
- -genomics
- -metabolomics
- -proteomics
- -vacciomics

Text Review Methodology

Cohort

46,422 Medline Publications
- include abstract and title
- 53,241,104 characters
- 6,069,011 words
- 126,968 unique words
- >90% of total words from 8153 unique words

the # of phrases is very, very, large and non manageable
- When a unique word was reviewed, other better spelled or short phrases were counted
- In addition, prior years phrases were counted (i.e. manually selected phrases)

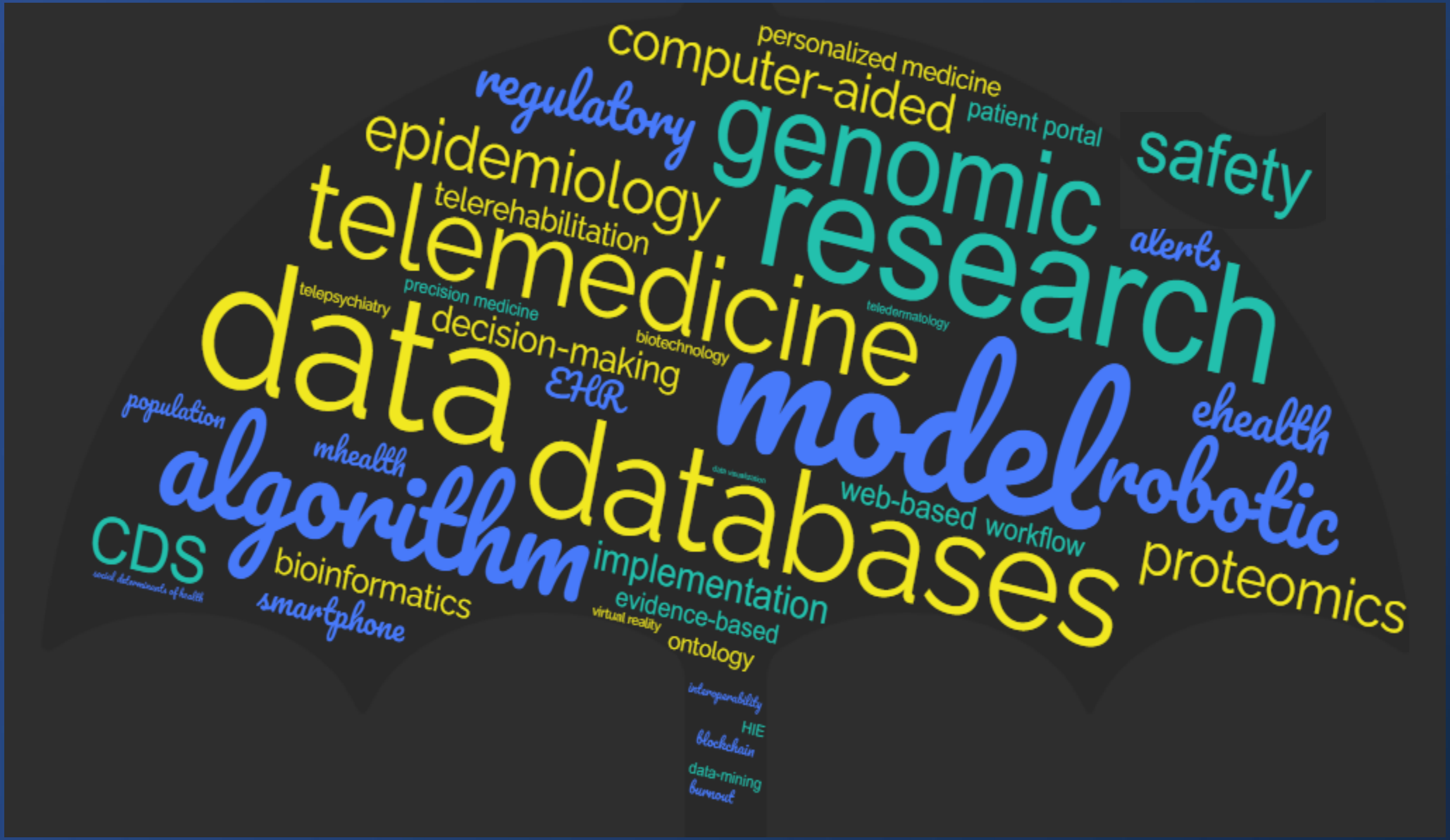
Phrases and words were counted in R and Adobe Acrobat

the #1 most common word in this clinical informatics Corpus was “the”. After common irrelevant words thrown out, the #1 word became “patient(s)” ☺

Who has mentions in the "Corpus"

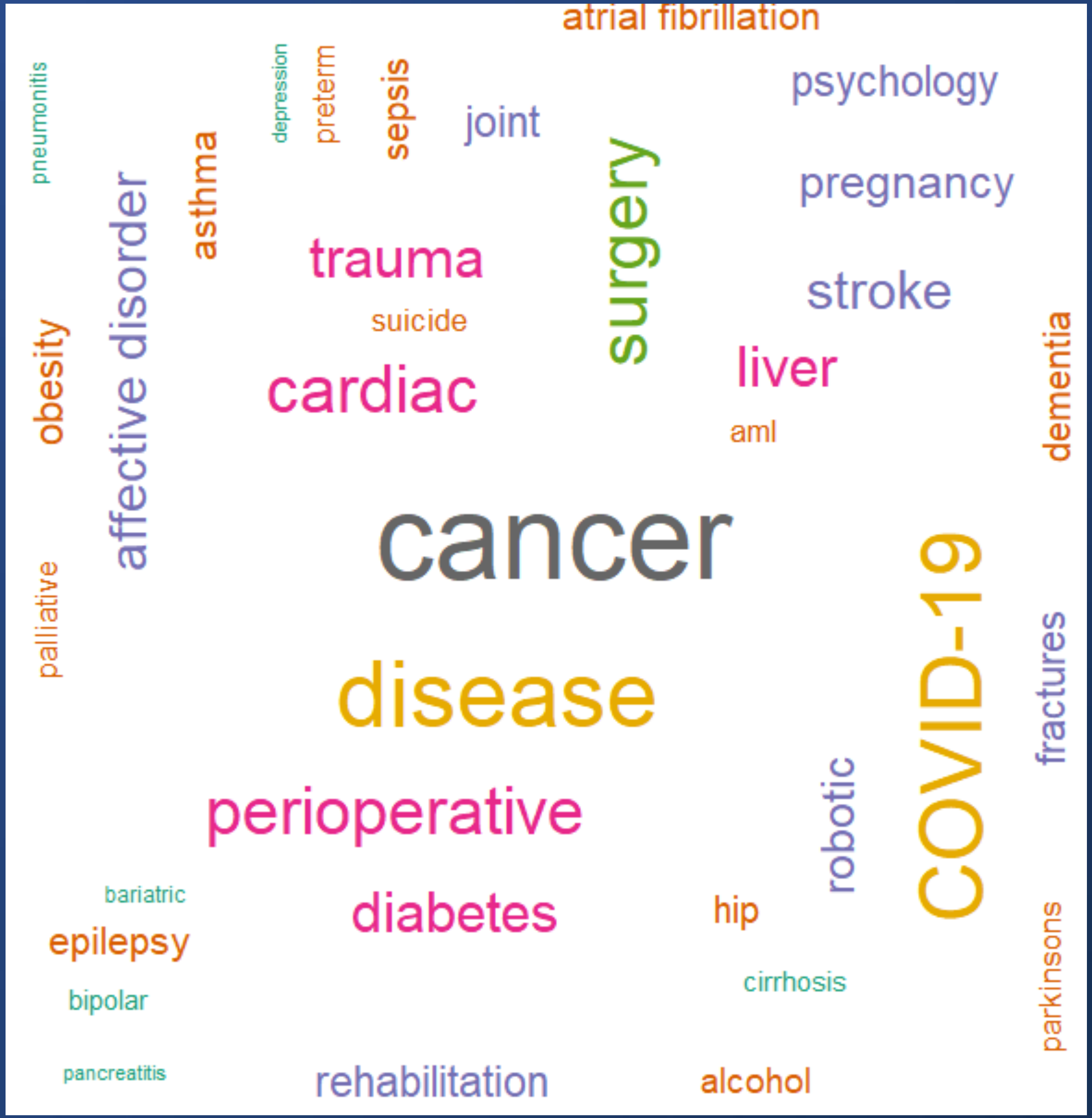
*log transformed

What are CI concepts in the "Corpus"



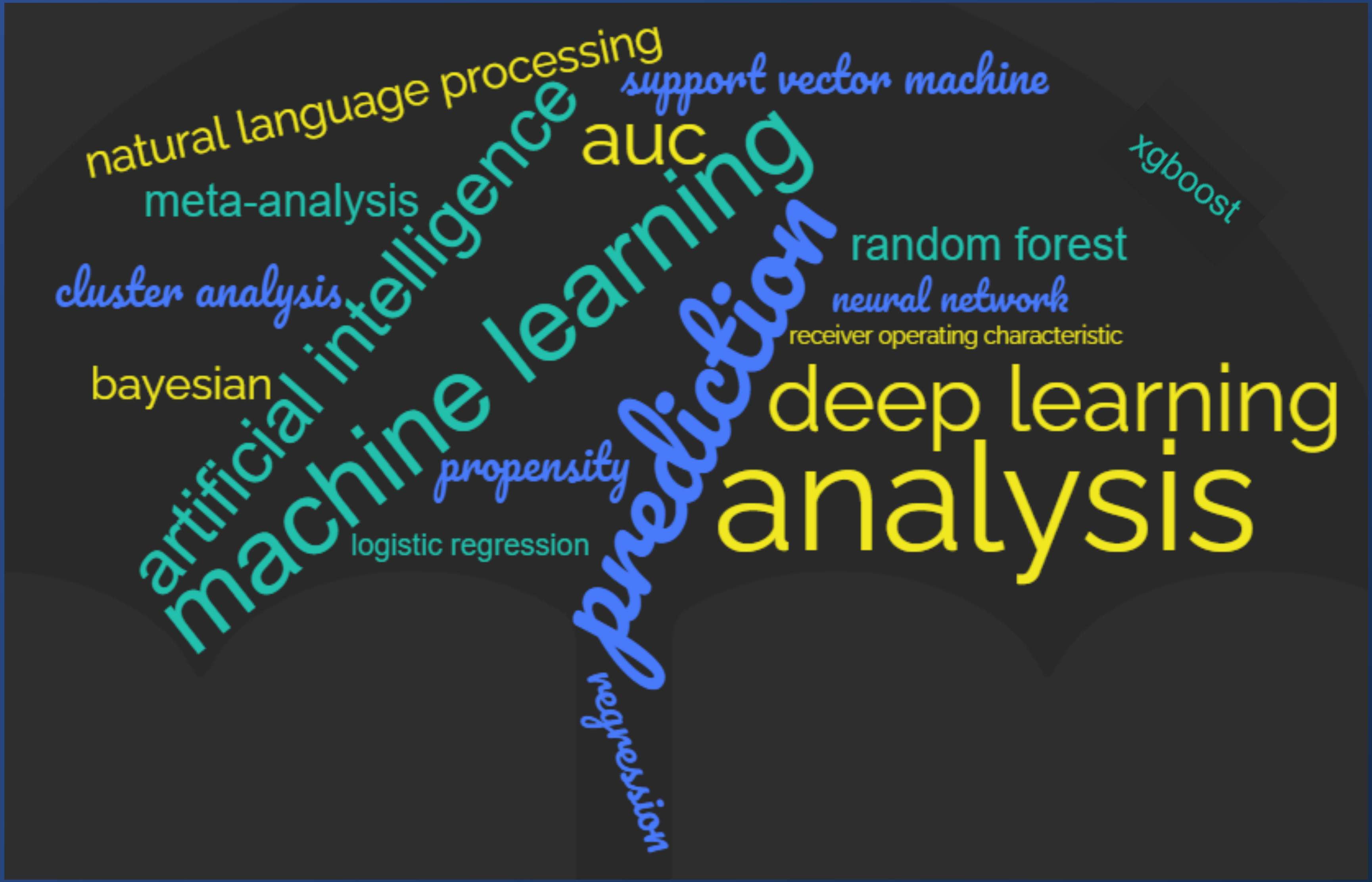
*log transformed

What diseases are in the "Corpus"



*log transformed

What *Analytic* concepts are in the Corpus?



*log transformed

Transition Slide –

Inboxes

GomerBlog @GomerBlog · Dec 24, 2020

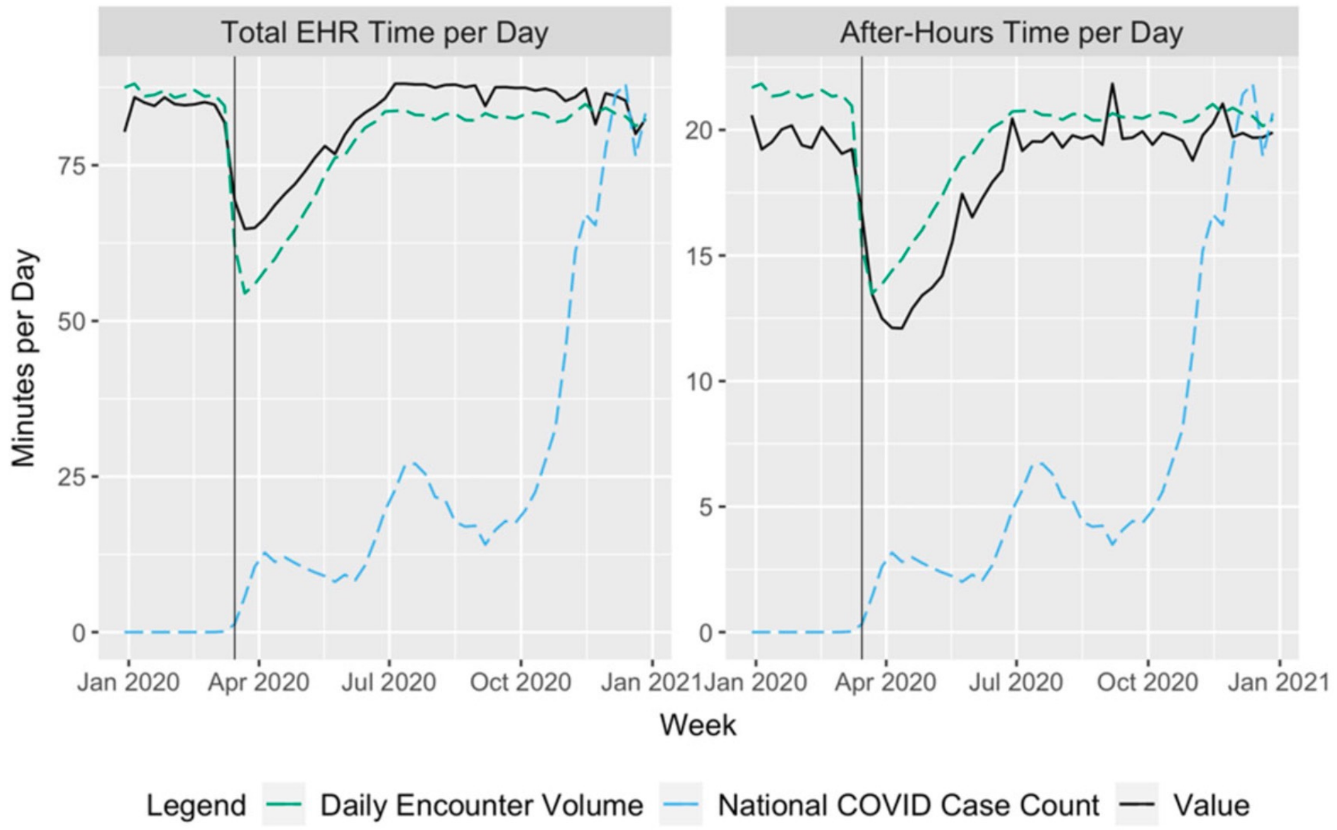
Doctors May Qualify for Law Degree After Completing HIPAA and EMTALA Compliance Training - gomerblog.com/2020/11/doctor… #foamed

2

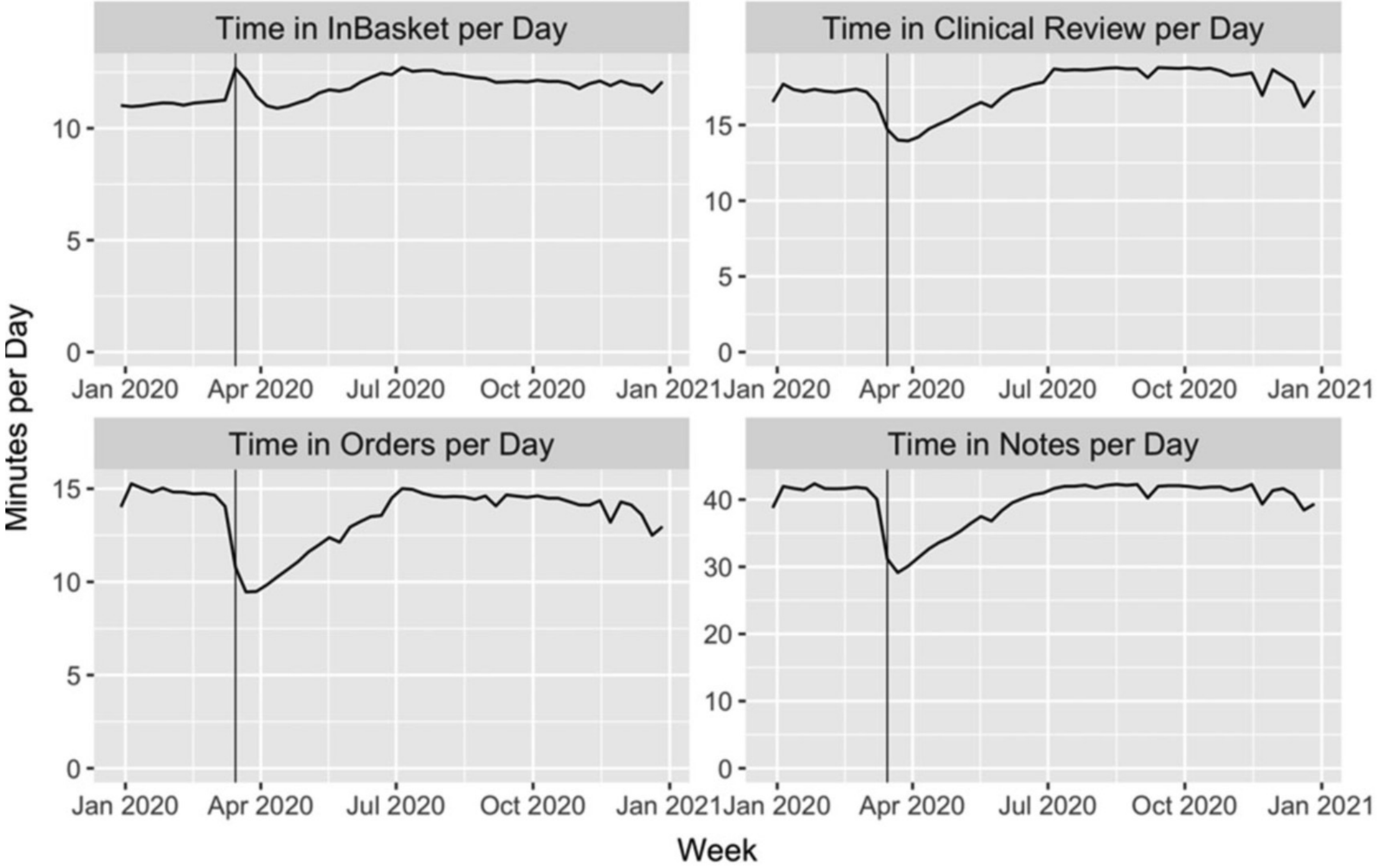
Assessing the impact of the COVID-19 pandemic on clinician ambulatory electronic health record use

A. Jay Holmgren[1], N. Lance Downing[2], Mitchell Tang[3,4], Christopher Sharp[2], Christopher Longhurst[1], and Robert S. Huckman[4]

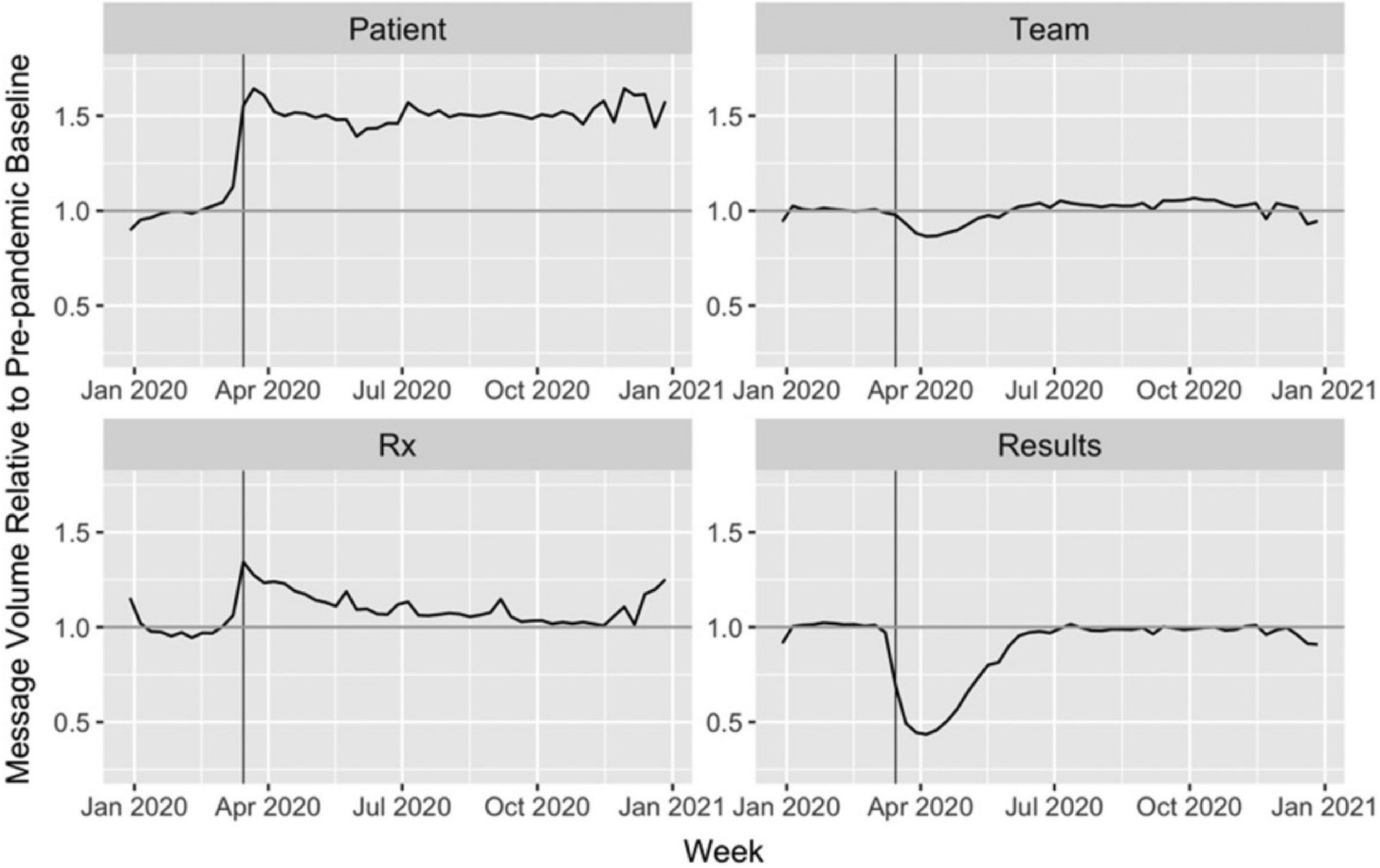
- JAMIA November 2021
- UC System and Mass Gen Brig
- Using Epic Signal Data from 366 health systems December 2019-December 2020
- For Ambulatory Encounters: Active time in EHR / Time After-Hours / Time in in-basket / Clinical Review / Notes / Results



https://doi.org/10.1093/jamia/ocab268



Time in InBasket per Day
Time in Clinical Review per Day
Time in Orders per Day
Time in Notes per Day
Minutes per Day
Week
0
5
10
15
20
30
40
Jan 2020
Apr 2020
Jul 2020
Oct 2020
Jan 2021


Patient
Team
Rx
Results
Message Volume Relative to Pre-pandemic Baseline
1.5
1.0
0.5
Jan 2020
Apr 2020
Jul 2020
Oct 2020
Jan 2021
Week

EHR Usage During and After COVID

- Clinical Review and In-Basket biggest drivers of increased EHR time
- Patient Messages up 157% from pre-pandemic levels
- Telehealth begets portal enrollment and comfort with portal messaging
- Even when telehealth subsided messages stayed elevated
- Each patient message translates to 2.3 additional minutes in the EHR

https://doi.org/10.1093/jamia/ocab268

Research Letter | Health Policy

Association of Immediate Release of Test Results to Patients With Implications for Clinical Workflow

Bryan D. Steitz, PhD; Lina Sulieman, PhD; Adam Wright, PhD; Samuel Trent Rosenbloom, MD

JAMA Network Open

- Vanderbilt – Epic System 1000 beds
- Measured rates at which patients viewed their test results in the patient portal before their clinician
- Measured percentage of tests seen by patients before being seen by clinicians in the EHR and were stratified by the historic release delay categories: immediate release, or held for release after a 1-day, 3-day, 7-day, or 14-day delay.
- Compared number of patient-initiated messages sent to clinicians within 6 hours of reviewing a result before and after the transition to Cures Act compliance.

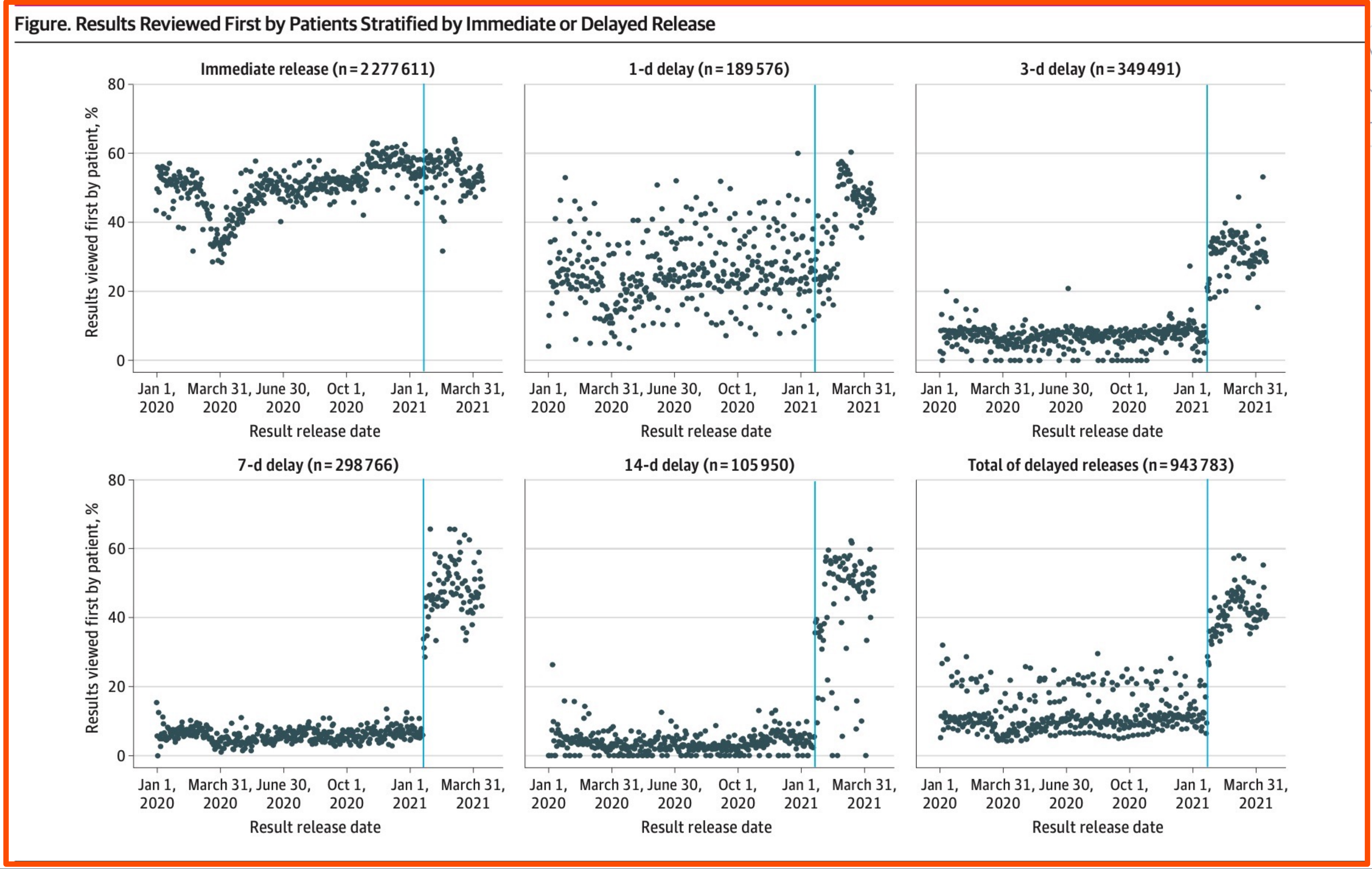


Figure. Results Reviewed First by Patients Stratified by Immediate or Delayed Release
Immediate release (n = 2 277 611)
1-d delay (n = 189 576)
3-d delay (n = 349 491)
7-d delay (n = 298 766)
14-d delay (n = 105 950)
Total of delayed releases (n = 943 783)
Results viewed first by patient, %
80
60
40
20
0
Jan 1, 2020
March 31, 2020
June 30, 2020
Oct 1, 2020
Jan 1, 2021
March 31, 2021
Result release date

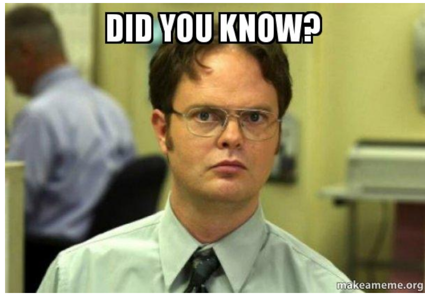
Patients see them before you… and they let you know

Results

- Prior to 21st Century Cures implementation 10.4% of results were seen by patients prior to clinicians
- After: 40.3% of results were seen by patients prior to clinicians

Messaging

- Prior to 21st Century Cures average volume of patient messaging within 6 hours of result view was 79 per day
- After: 146 messages per day



Transition Comedy Slide – COVID and Sepsis

The US is crippled by a hodgepodge health data infrastructure

(Talking about HIE for 20 years at AMDIS/AMIA has helped a little)

UK 67 Million People
USA 330 Million

the UK is not

Article

Factors associated with COVID-19-related death using OpenSAFELY

https://doi.org/10.1038/s41586-020-2521-4

Received: 15 May 2020

Accepted: 1 July 2020

Published online: 8 July 2020

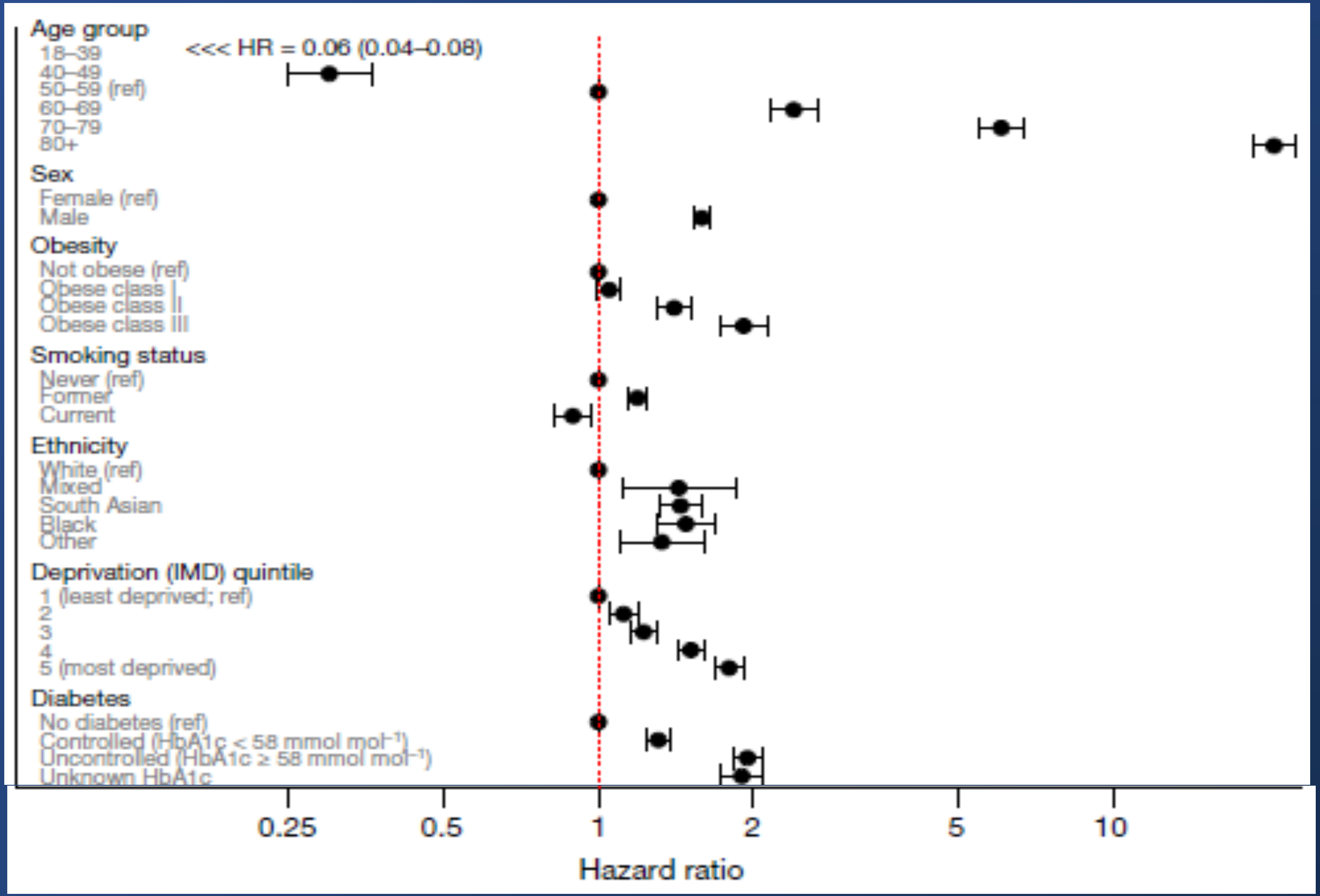
Elizabeth J. Williamson[1,6], Alex J. Walker[2,6], Krishnan Bhaskaran[1,6], Seb Bacon[2,6], Chris Bates[3,6], Caroline E. Morton[2], Helen J. Curtis[2], Amir Mehrkar[2], David Evans[2], Peter Inglesby[2], Jonathan Cockburn[3], Helen I. McDonald[1,4], Brian MacKenna[2], Laurie Tomlinson[1], Ian J. Douglas[1], Christopher T. Rentsch[1], Rohini Mathur[1], Angel Y. S. Wong[1], Richard Grieve[1], David Harrison[5], Harriet Forbes[1], Anna Schultze[1], Richard Croker[2], John Parry[3], Frank Hester[3], Sam Harper[3], Rafael Perera[2], Stephen J. W. Evans[1], Liam Smeeth[1,4,7] & Ben Goldacre[2,7] ✉

Factors associated with death in the UK

17.3 Million Patients
10,926 deaths

Williamson EJ, Walker AJ, Bhaskaran K, et al. Factors associated with COVID-19-related death using OpenSAFELY. Nature. 2020 Aug;584(7821):430-436. doi: 10.1038/s41586-020-2521-4. Epub 2020 Jul 8. PMID: 32640463

The risk of death from COVID in the UK



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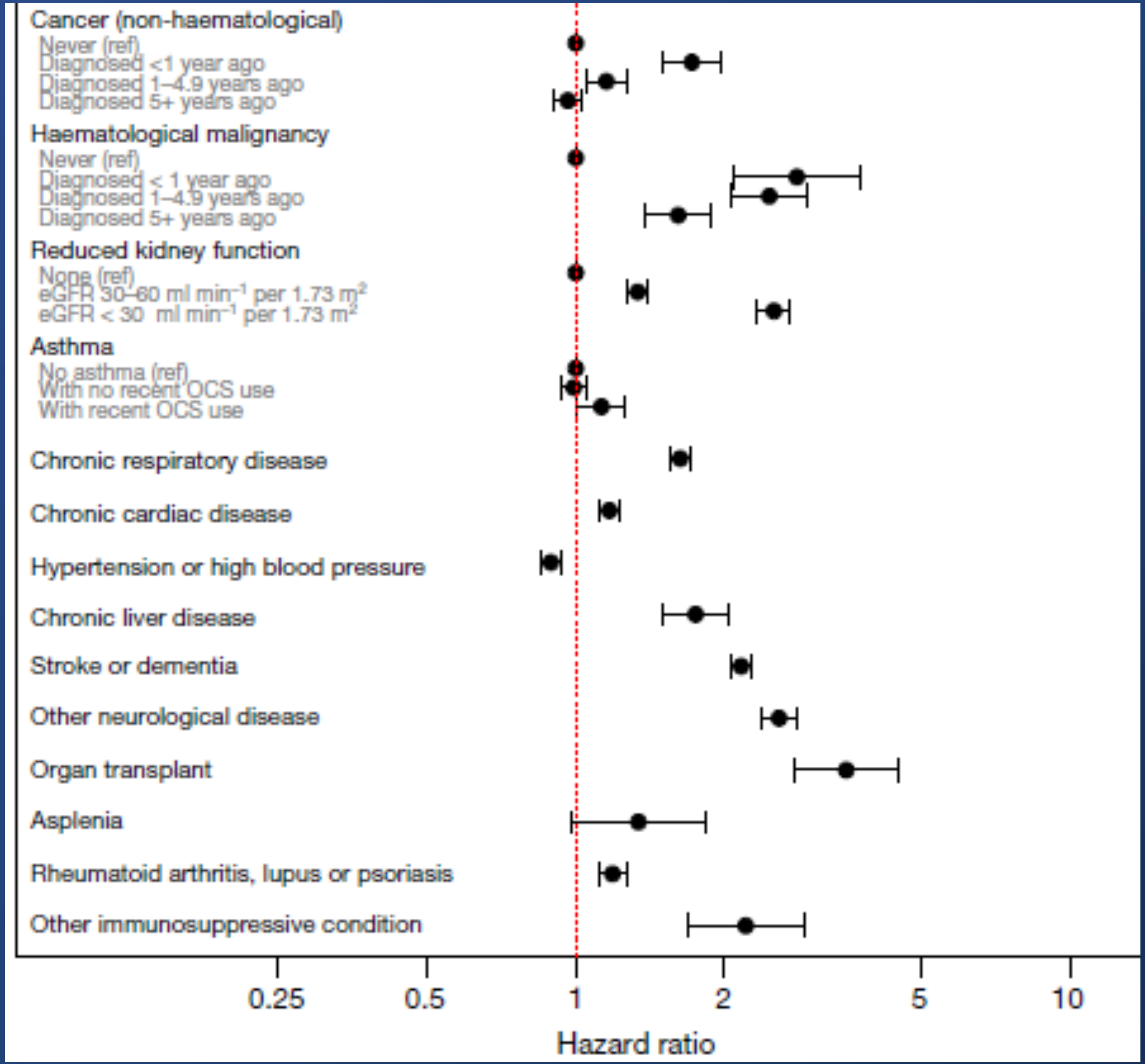

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The risk of death with COVID in the UK

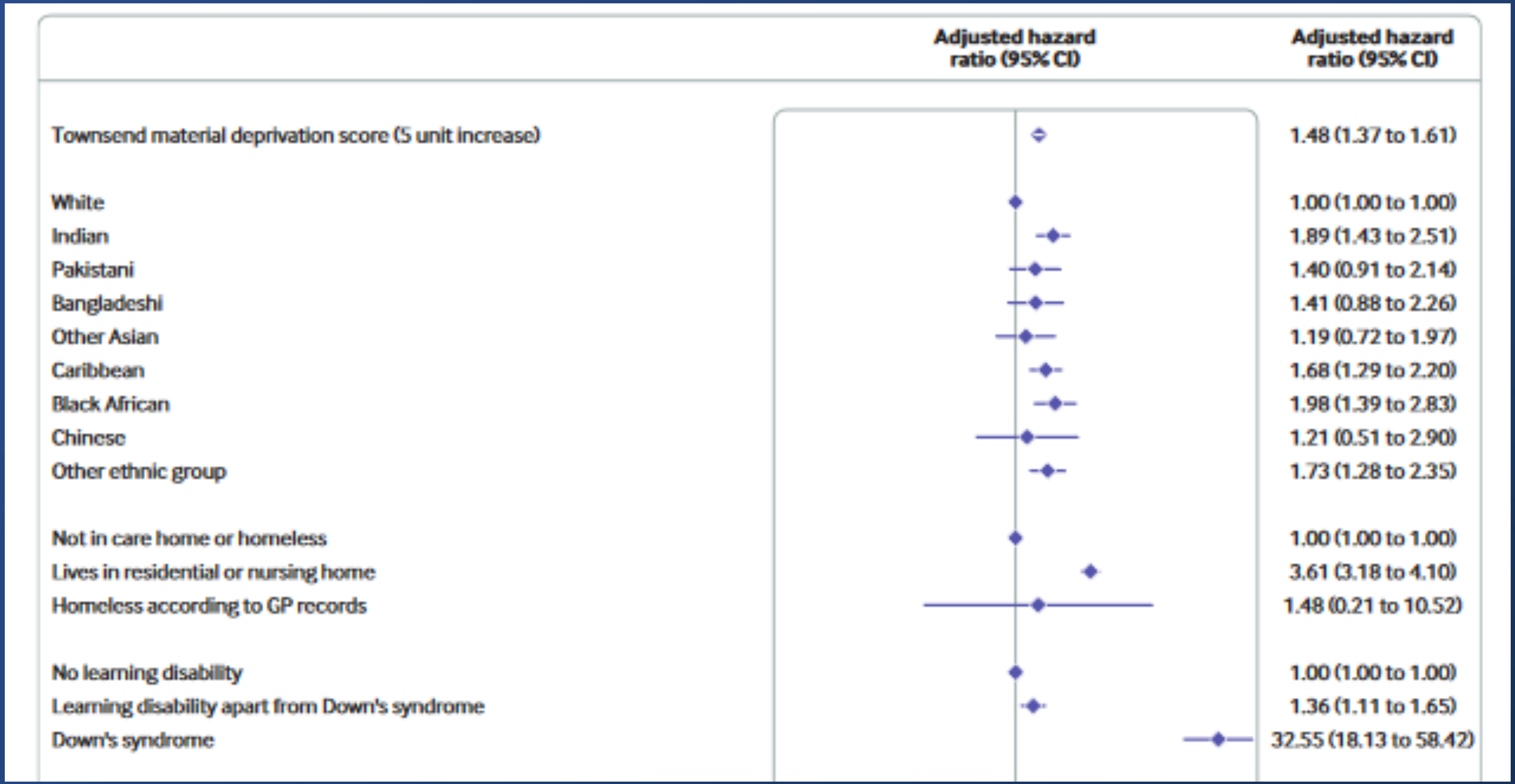
An external validation of the QCovid risk prediction algorithm for risk of mortality from COVID-19 in adults: a national validation cohort study in England

Vahé Nafilyan, Ben Humberstone, Nisha Mehta, Ian Diamond, Carol Coupland, Luke Lorenzi, Piotr Pawelek, Ryan Schofield, Jasper Morgan, Paul Brown, Ronan Lyons, Aziz Sheikh, Julia Hippisley-Cox

Model for COVID mortality:	Derivation:	6.1 Million
	Validation:	2.17 Million[1]
	External Validation:	34.9 Million[2]

1 Clift AK, Coupland CAC, Keogh RH, et al. Living risk prediction algorithm (QCOVID) for risk of hospital admission and mortality from coronavirus 19 in adults: national derivation and validation cohort study. BMJ. 2020 Oct 20;371:m3731. doi: 10.1136/bmj.m3731. PMID: 33082154.
2 Nafilyan V, Humberstone B, Mehta N, et al.. An external validation of the QCovid risk prediction algorithm for risk of mortality from COVID-19 in adults: a national validation cohort study in England. Lancet Digit Health. 2021 Jul;3(7):e425-e433. doi: 10.1016/S2589-7500(21)00080-7. Epub 2021 May 25. PMID: 34049834

The risk of death with COVID in the UK



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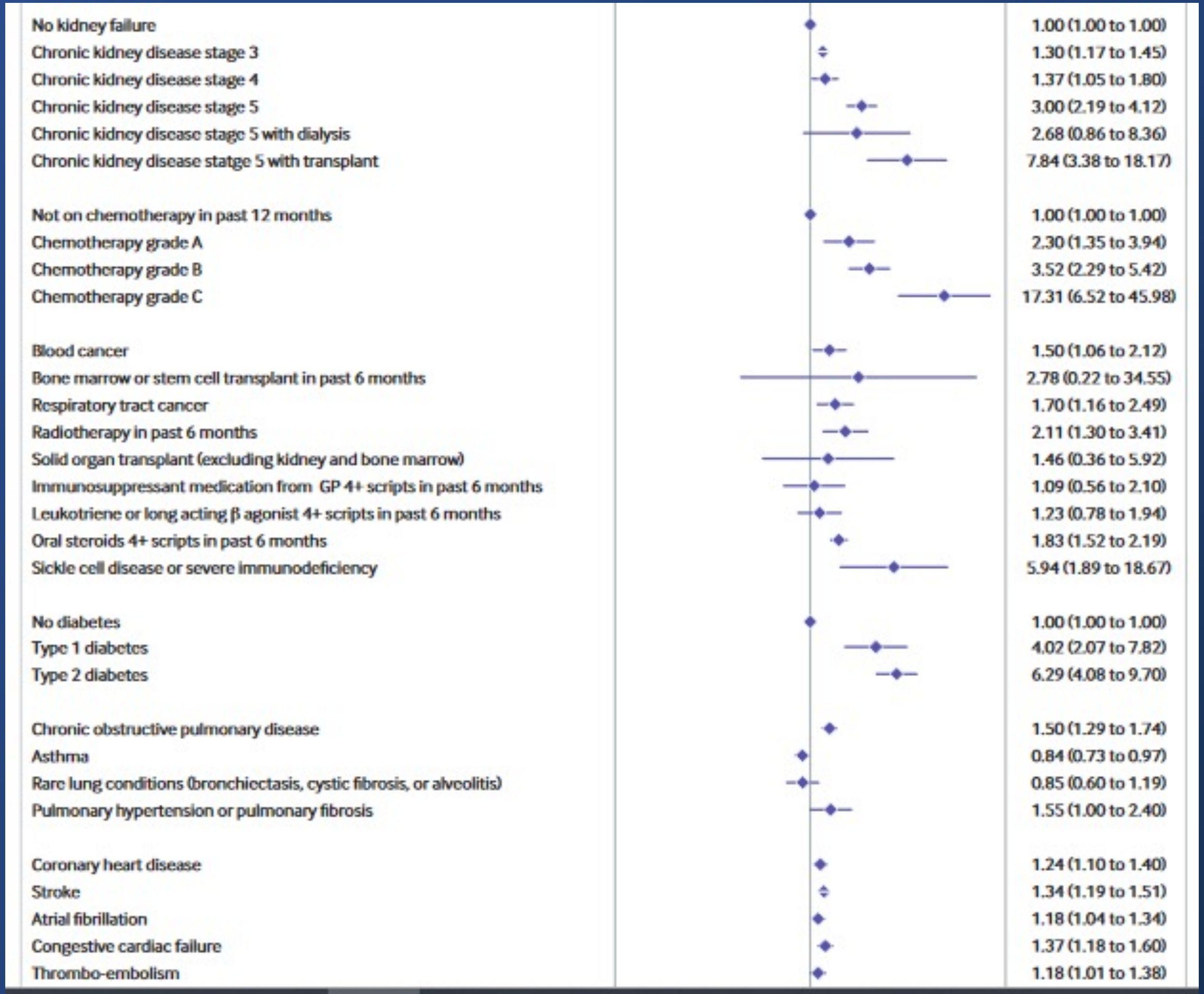

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Trusting other people's AI

JAMA Internal Medicine | Original Investigation

External Validation of a Widely Implemented Proprietary Sepsis Prediction Model in Hospitalized Patients

Andrew Wong, MD; Erkin Otles, MEng; John P. Donnelly, PhD; Andrew Krumm, PhD; Jeffrey McCullough, PhD;
Olivia DeTroyer-Cooley, BSE; Justin Pestrue, MEcon; Marie Phillips, BA; Judy Konye, MSN, RN;
Carleen Penoza, MHSA, RN; Muhammad Ghous, MBBS; Karandeep Singh, MD, MMSc

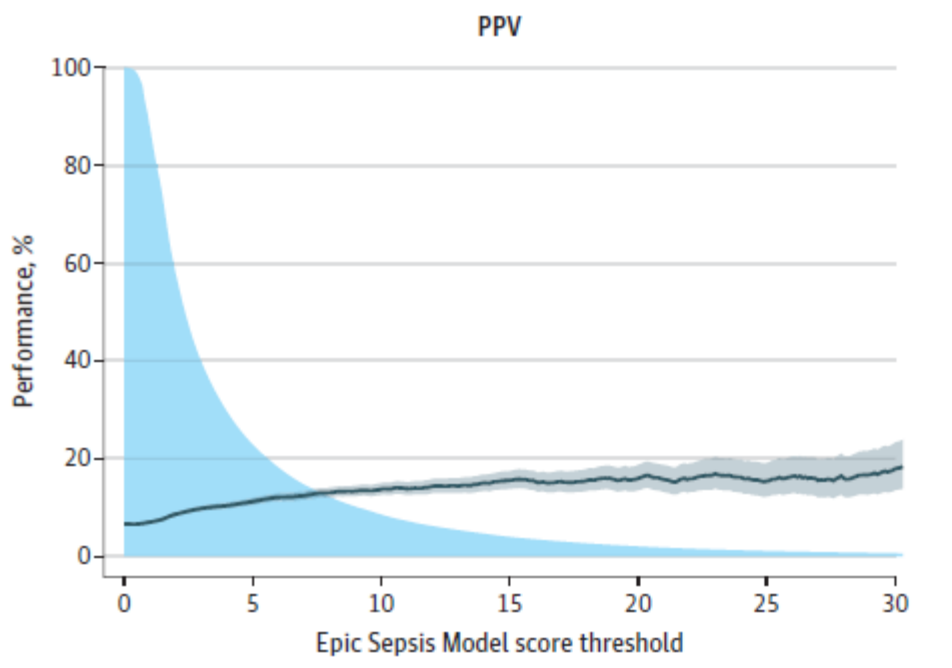
-Epic Sepsis Model is being used at many sites
-Is part of the Epic "foundation", so recommended
-Very annoying to inpatient clinicians (***Informal feedback)***

How does it work?

- -Single site external validation
- -27,697 unique patients during 38,455 hospitalizations

Wong A, Otles E, Donnelly JP, et al. External Validation of a Widely Implemented Proprietary Sepsis Prediction Model in Hospitalized Patients. JAMA Intern Med. 2021 Aug 1;181(8):1065-1070. doi: 10.1001/jamainternmed.2021.2626. Erratum in: JAMA Intern Med. 2021 Aug 1;181(8):1144. PMID: 34152373

Trusting other people's AI



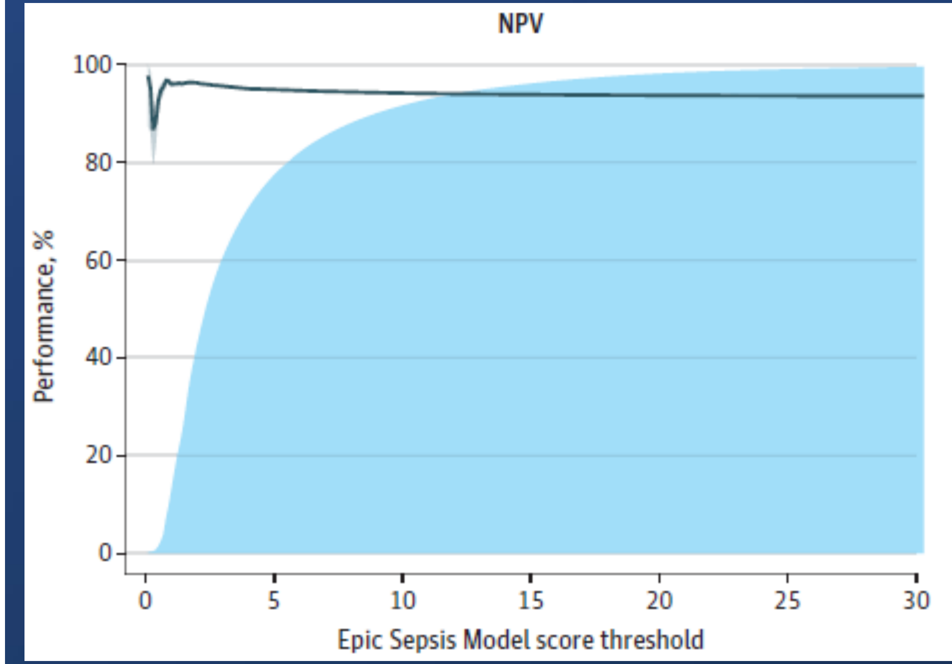


Table 2. ESM Performance

		Time horizons			
Model performance	Hospitalization	24 h	12 h	8 h	4 h
Outcome incidence, %	6.6	0.43	0.29	0.22	0.14
Area under the receiver operating characteristic curve (95% CI)	0.63 (0.62-0.64)	0.72 (0.72-0.72)	0.73 (0.73-0.74)	0.74 (0.74-0.75)	0.76 (0.75-0.76)
Positive predictive value (ESM score ≥6), %	12	2.4	1.7	1.4	0.92
No. needed to evaluate (ESM score ≥6)[a]	8	42	59	73	109

Wong A, Otles E, Donnelly JP, et al. External Validation of a Widely Implemented Proprietary Sepsis Prediction Model in Hospitalized Patients. JAMA Intern Med. 2021 Aug 1;181(8):1065-1070. doi: 10.1001/jamainternmed.2021.2626. Erratum in: JAMA Intern Med. 2021 Aug 1;181(8):1144. PMID: 34152373

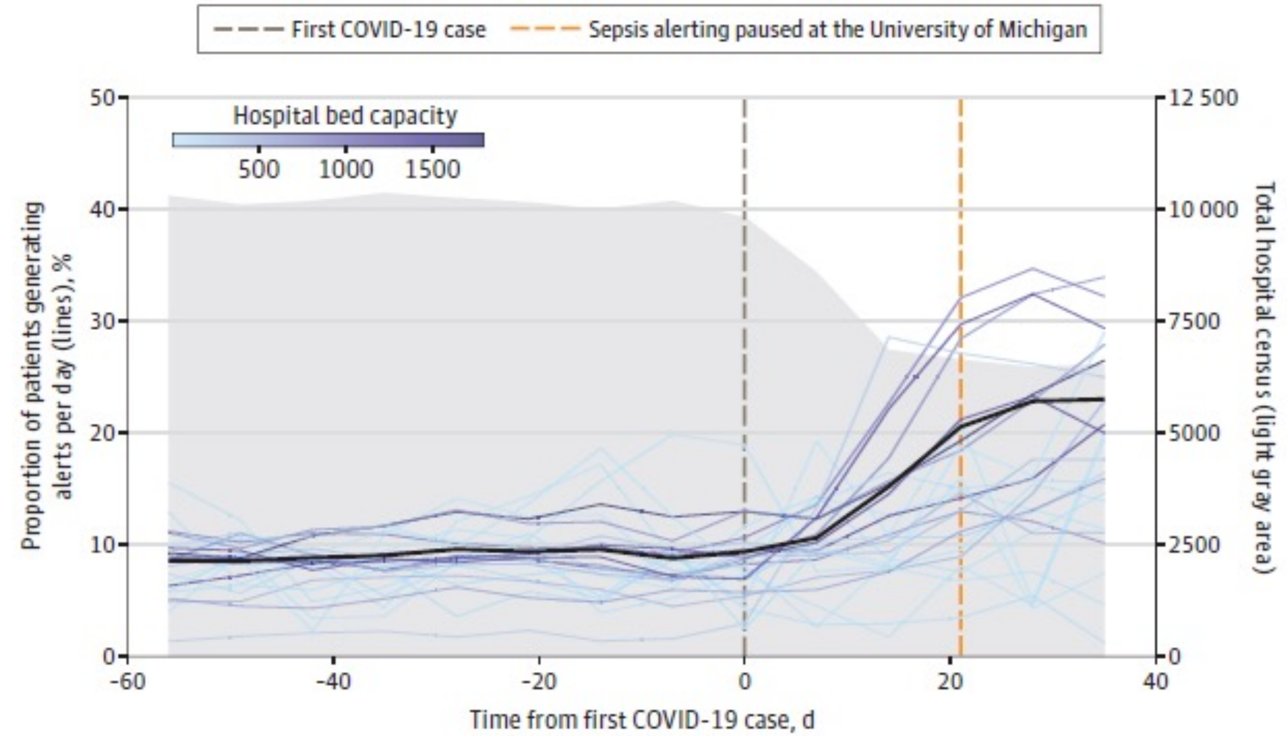
Trusting other people's AI on different patients

Research Letter | Health Informatics

Quantification of Sepsis Model Alerts in 24 US Hospitals Before and During the COVID-19 Pandemic

Andrew Wong, MD; Jie Cao, MPH; Patrick G. Lyons, MD, MSc; Sayon Dutta, MD, MPH; Vincent J. Major, PhD; Erkin Ötleş, MEng; Karandeep Singh, MD, MMSc

Figure. Comparison of Total Hospital Census and Proportion of Patients Generating Sepsis Alerts at Each Hospital, Aligned by Hospitals' First Case of COVID-19



Wong A, Cao J, Lyons PG, Dutta S, Major VJ, Ötles E, Singh K. Quantification of Sepsis Model Alerts in 24 US Hospitals Before and During the COVID-19 Pandemic. JAMA Netw Open. 2021 Nov 1;4(11):e2135286. doi: 10.1001/jamanetworkopen.2021.35286.

Sepsis AI was a hot topic

The Epic Sepsis Model Falls Short—The Importance of External Validation

Anand R. Habib, MD, MPhil; Anthony L. Lin, MD; Richard W. Grant, MD, MPH

Digital medicine

Digitising the prediction and management of sepsis

The Lancet April 2022 - Topol

VIEWPOINT

Preparing Clinicians for a Clinical World Influenced by Artificial Intelligence

JAMA March 2022 – James, Wachter et al

EHR Data Mining in the COVID era

Relation of prior statin and anti-hypertensive use to severity of disease among patients hospitalized with COVID-19: Findings from the American Heart Association's COVID-19 Cardiovascular Disease Registry

Lori B. Daniels[1,2]*, Junting Ren[3‡], Kris Kumar[4], Quan M. Bui[1], Jing Zhang[5], Xinlian Zhang[3], Mariem A. Sawan[6], Howard Eisen[7], Christopher A. Longhurst[8], Karen Messer[3,5]

PLOS ONE

Resurgence of SARS-CoV-2 Infection in a Highly Vaccinated Health System Workforce

The NEW ENGLAND JOURNAL of MEDICINE

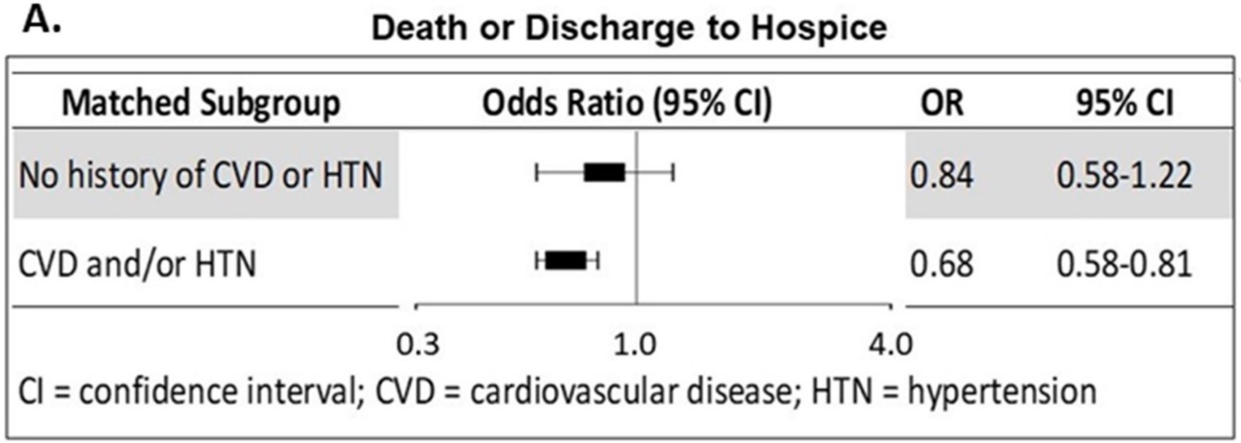
Statins and COVID

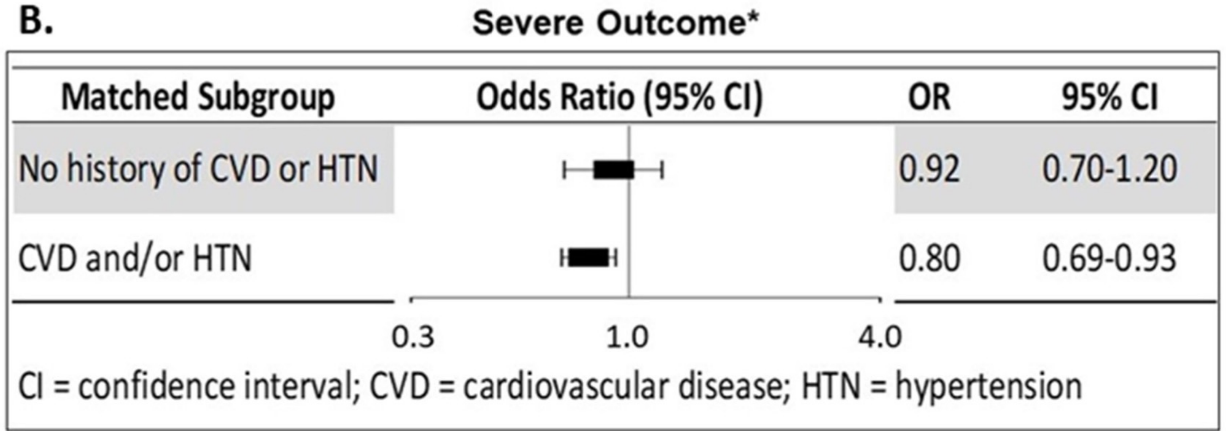
- 10.5K COVID patients across 104 hospitals enrolled in the AHA registry
- Analyze the effect of statins / statin + anti-HTN on outcomes such as death or severe outcome

<u>Yup – statins matter; especially for patients with pre-existing disease</u>

Anti-inflammatory properties of statins

RCTs on statins and COVID underway





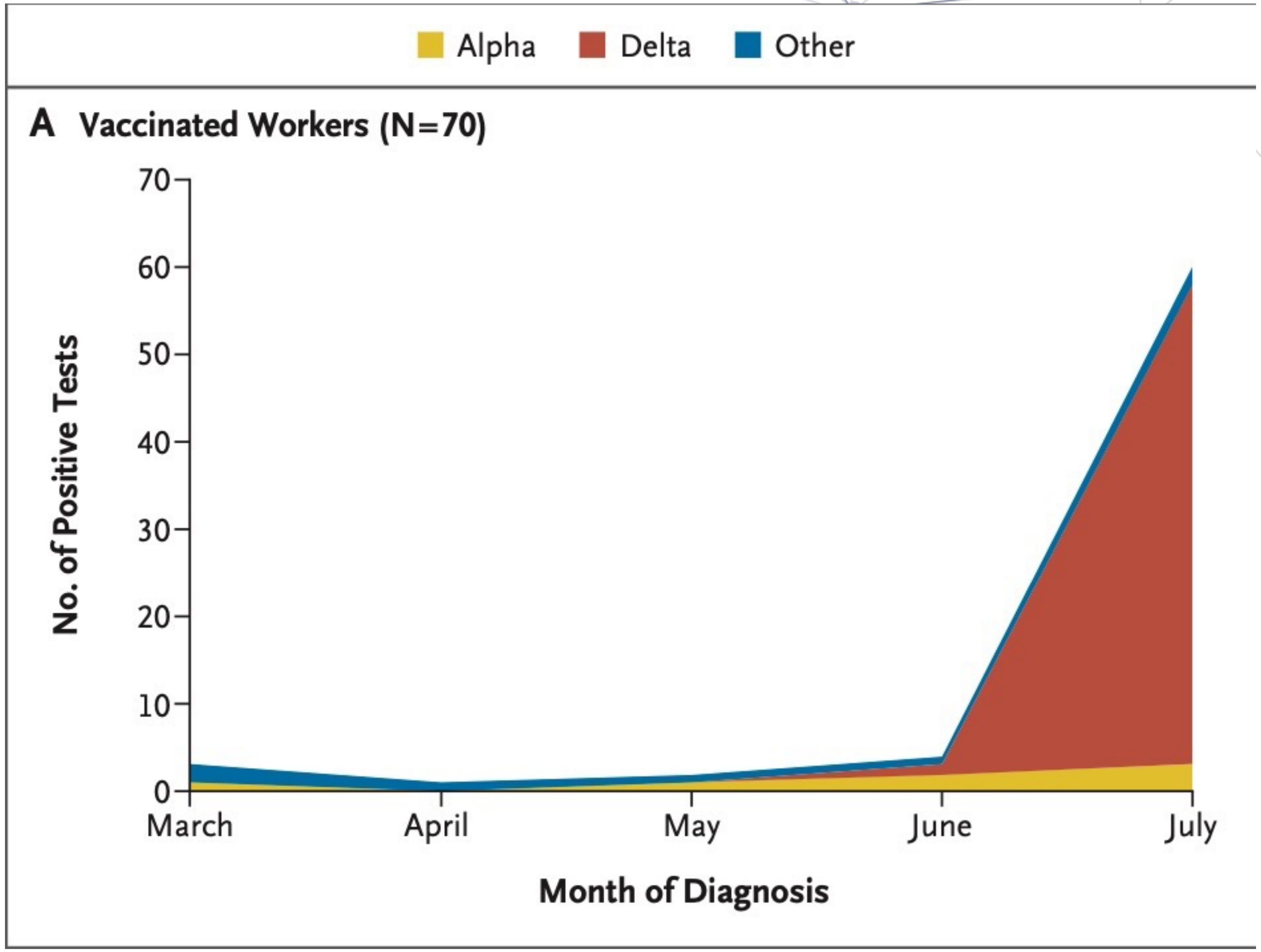
Internal Data showing COVID Re-Infection

When Delta hit

- If you had completed in Jan-Feb reinfection was 6.7 per 1000
- Mar-May was 3.7 per 1000
- Non-vax was 16.4 per 1000

This was eventually cited by the FDA and CDC in their booster shot deliberations September 2021; eventually informed the recommendations for health care providers to get the booster

Also showed potential impact of lifting of social distancing changes at the time as well



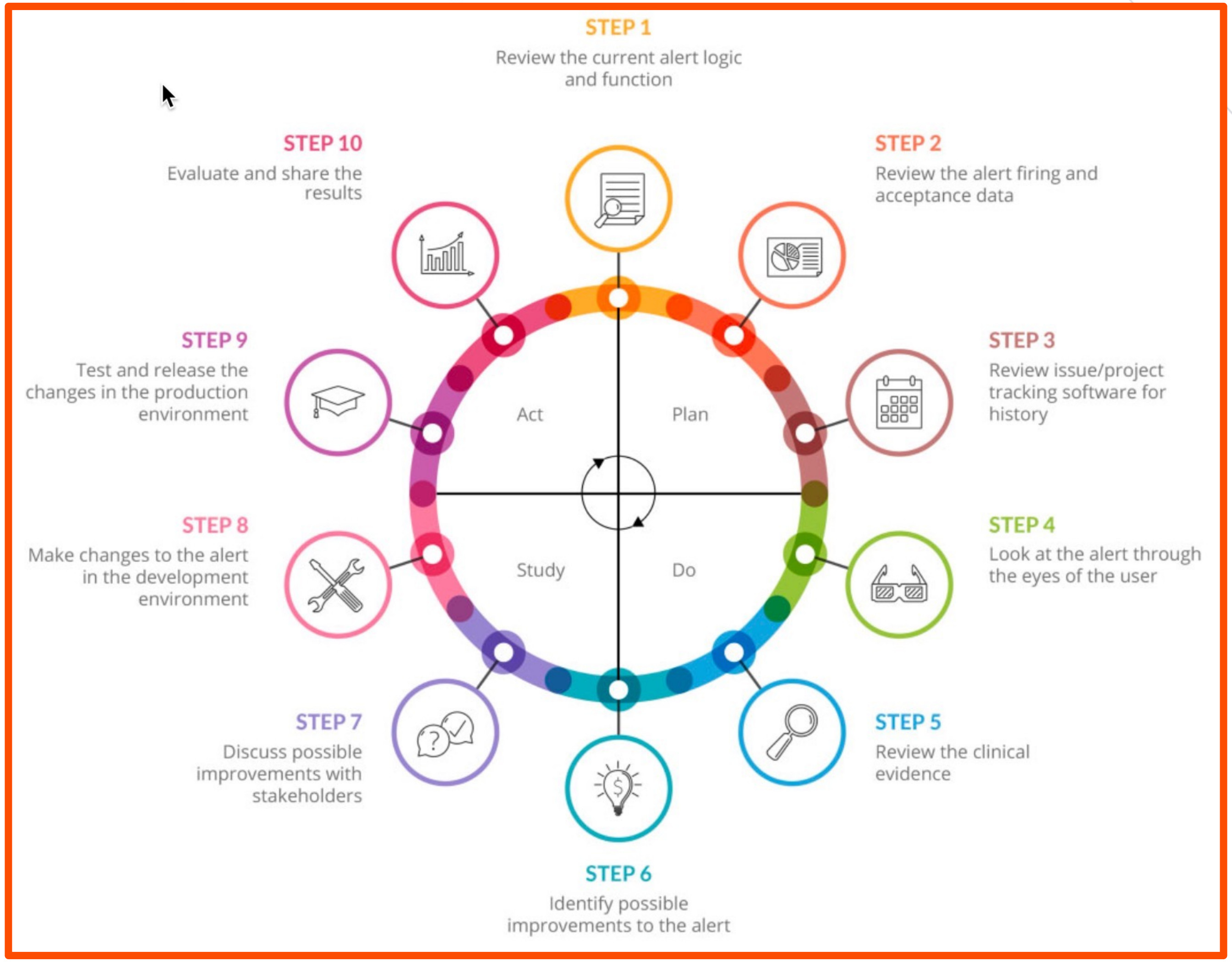
Transition Comedy Slide:

Burnout

Clinician collaboration to improve clinical decision support: the Clickbusters initiative

Allison B. McCoy[1,2], Elise M. Russo[1], Kevin B. Johnson[1,2,3], Bobby Addison[2], Neal Patel[1,2,3], Jonathan P. Wanderer[1,2,4], Dara E. Mize[1,2,5], Jon G. Jackson[2], Thomas J.

- Vanderbilt (1000 beds / 2M op visits / Epic 2017) effort to optimize CDS with an eye towards reducing burnout and clicks
- Utilizing Physician Builders first, then interested parties
- Built a curriculum to educate the newly interested
- Tracking and scoring mechanisms – Burden and Complexity
- Gamification and rewards for the participants



ClickBusters

2 rounds of busting – 3 months each

	Round 1	Round 2	Total
Participants	8	20	24
Alert groups	18	24	42
Total alerts analyzed	29	55	84
Alerts with no modifications needed	12	20	32
Alerts with modifications	13	29	42
Alerts turned off	4	6	10
Weekly clicks busted	49 026	22 201	71 227

ClickBusters !

Burden Score – based on firing rates / override and acceptance rates – score of 1-10

Complexity Score – based on the logic statements and restrictions, invoking data, and knowledge content - score of 1-10

Baseline - 419 BPA / ~500k firings per week / ~43k interruptive

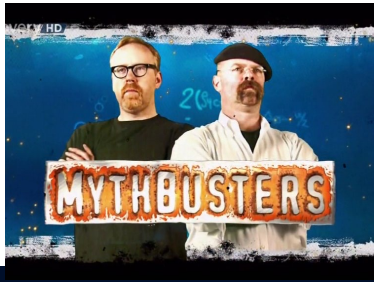
<u>The so what:</u>

A novel approach to evaluating and optimizing CDS alerts

Involved "new blood" and invested parties to teach them how to evaluate and re-think decision support

Gamification in performance improvement

A step beyond standard dashboards for CDS



A qualitative study of provider burnout: do medical scribes hinder or help?

Sky Corby[1], Joan S. Ash[2], Vishnu Mohan[2], James Becton[2], Nicholas Solberg[1], Robby Bergstrom[2], Benjamin Orwoll[2,3], Christopher Hoekstra[2], and Jeffrey A. Gold[1]

They help.

JAMIA
A SCHOLARLY JOURNAL OF INFORMATICS IN HEALTH AND BIOMEDICINE

BMC Medical Informatics and Decision Making

The future of medical scribes documenting in the electronic health record: results of an expert consensus conference

Sky Corby[1*], Keaton Whittaker[2], Joan S. Ash[2], Vishnu Mohan[2], James Becton[2], Nicholas Solberg[1], Robby Bergstrom, Benjamin Orwoll[2,3], Christopher Hoekstra[2] and Jeffrey A. Gold[1]

OHSU as corresponding authors

- Interviews and observations followed by 2 day conference for 5 health systems using scribes
- Summarizes current state of the industry
- Define potential regulatory implications , threats, and opportunities for scribes
- For any health system using scribes this is a great think piece regarding the industry as well as ideas to run your program

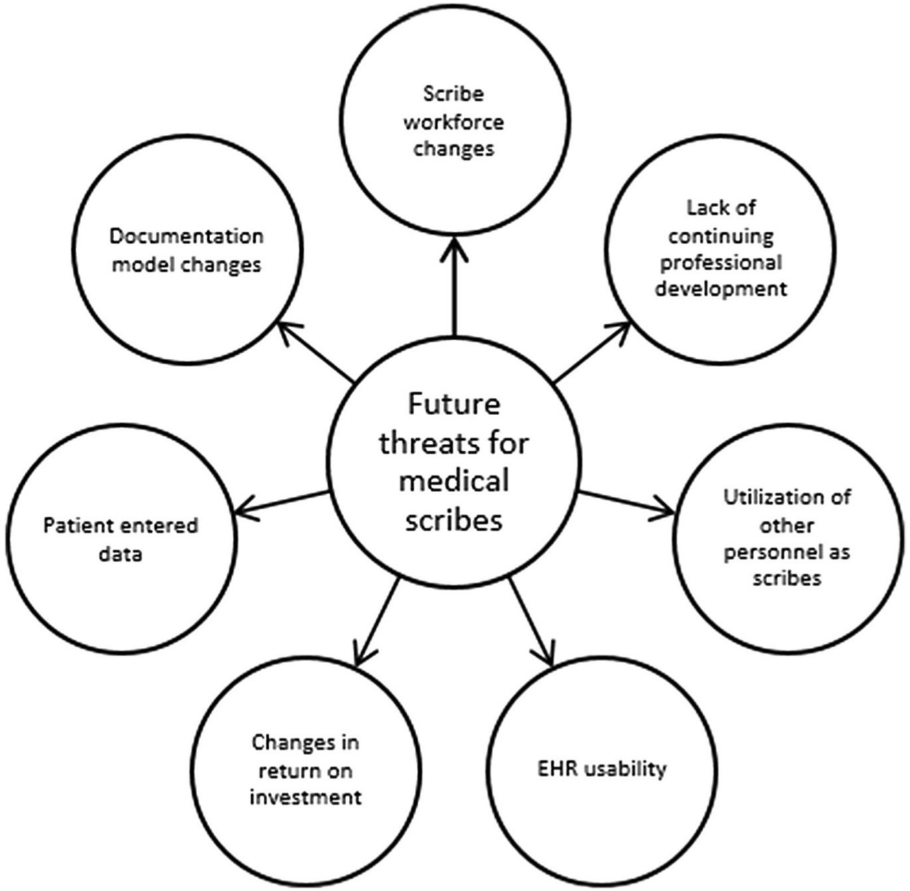


Fig. 1 Threats to future of medical scribes

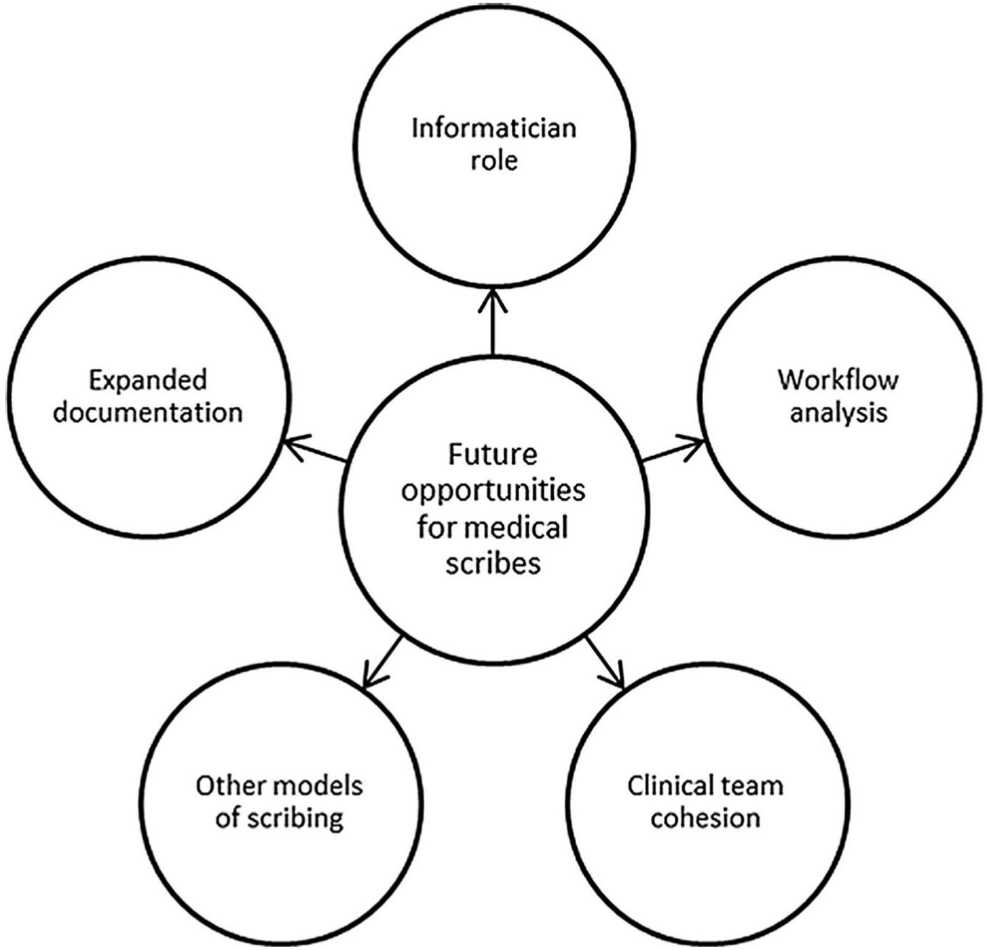


Fig. 2 Opportunities for the future of medical scribes

Prophylactic EHR switch anxiety prevention

RESEARCH ARTICLE

The impact of Stress Management and Resilience Training (SMART) on academic physicians during the implementation of a new Health Information System: An exploratory randomized controlled trial

Edward G. Spilg[1,2]*, Hanna Kuk[1], Lesley Ananny[3], Kylie McNeill[1], Vicki LeBlanc[3], Brent A. Bauer[4], Amit Sood[4], Philip S. Wells[1,2]

-Canadian
-Randomized Controlled
-Smart® intervention[2]
-Small

Spilg EG, Kuk H, Ananny L, et al. The impact of Stress Management and Resilience Training (SMART) on academic physicians during the implementation of a new Health Information System: An exploratory randomized controlled trial. PLoS One. 2022 Apr 22;17(4):e0267240. doi: 10.1371/journal.pone.0267240. PMID: 35452478
2 Sood A, Prasad K, Schroeder D, Varkey P. Stress management and resilience training among Department of Medicine faculty: a pilot randomized clinical trial. J Gen Intern Med. 2011 Aug;26(8):858-61. doi: 10.1007/s11606-011-1640-x. Epub 2011 Jan 29. PMID: 21279454

Prophylactic EHR switch anxiety prevention

	6-months follow-up (N = 32)		
Outcome	**LSMD**	**95% CI**	***p*-value**
Resilience (CD-RISC)	4.85	-0.81, 10.05	0.090
Subjective Happiness (SHS)	0.23	-0.23, 0.69	0.316
Stress (PSS)	-4.83	-10.85, 1.19	0.111
Anxiety (GAD-7)			
Log-Scale	-0.25	-0.52, 0.02	0.068
Relative Difference[1]	0.56	0.30, 1.05	--

"no statistically significant intervention effect was observed for resilience, subjective happiness, stress or anxiety at 3-months or 6-months follow-up."

	Control		
	Baseline (N = 19)	**3-months follow-up (N = 17)**	**6-months follow-up (N = 16)**
Resilience (CD-RISC), M (SD)	68.42 (11.82)	66.59 (10.10)	66.88 (10.01)
Subjective Happiness (SHS), M (SD)	5.21 (0.98)	5.13 (0.92)	5.09 (1.01)
Stress (PSS), M (SD)	15.74 (4.02)	16.82 (5.39)	17.75 (7.81)
Anxiety (GAD-7), Md (IQR)	4.00 (2.00, 6.00)	5.00 (3.00, 8.75)	6.32 (2.21, 10.72)

My Conclusion

Switching your EHR increased physician stress and anxiety and reduced happiness 6 months later.

If you are told by the C-suite and people in suits that things will be better, have skepticism…

Spilg EG, Kuk H, Ananny L, et al. The impact of Stress Management and Resilience Training (SMART) on academic physicians during the implementation of a new Health Information System: An exploratory randomized controlled trial. PLoS One. 2022 Apr 22;17(4):e0267240. doi: 10.1371/journal.pone.0267240. PMID: 35452478

Transition – AI, CDS, and Telehealth

Computers can help clinicians look at images

Artificial intelligence-assisted colonoscopy: A prospective, multicenter, randomized controlled trial of polyp detection

Lei Xu[1] | Xinjue He[2] | Jianbo Zhou[3] | Jie Zhang[2] | Xinli Mao[4] | Guoliang Ye[5] | Qiang Chen[6] | Feng Xu[7] | Jianzhong Sang[3] | Jun Wang[4] | Yong Ding[5] | Youming Li[2] | Chaohui Yu[2]

-AI group did not show significant increment in polyp detection rate (38.8% vs. 36.2%, $p = 0.183$)

-AI group improved polyps per colonoscopy (0.5 vs. 0.4, $p < 0.05$)

-AI group detected more diminutive polyps (76.0% vs. 68.8%, $p < 0.01$) and flat polyps (5.9% vs. 3.3%, $p < 0.05$).

Xu L, He X, Zhou J, et al. Artificial intelligence-assisted colonoscopy: A prospective, multicenter, randomized controlled trial of polyp detection. Cancer Med. 2021 Oct;10(20):7184-7193. doi: 10.1002/cam4.4261. Epub 2021 Sep 3. PMID: 34477306

Computers can help clinicians look at images

Artificial intelligence

Original research

Artificial intelligence and colonoscopy experience: lessons from two randomised trials

Alessandro Repici,[1,2] Marco Spadaccini ,[1,2] Giulio Antonelli ,[3,4] Loredana Correale,[2] Roberta Maselli,[1,2] Piera Alessia Galtieri,[2] Gaia Pellegatta,[2] Antonio Capogreco,[1,2] Sebastian Manuel Milluzzo,[5] Gianluca Lollo,[6] Dhanai Di Paolo,[7] Matteo Badalamenti,[2] Elisa Ferrara,[2] Alessandro Fugazza ,[2] Silvia Carrara,[2] Andrea Anderloni,[2] Emanuele Rondonotti ,[7] Arnaldo Amato ,[7] Andrea De Gottardi,[6] Cristiano Spada,[5] Franco Radaelli ,[7] Victor Savevski,[8] Michael B Wallace,[9] Prateek Sharma,[10,11] Thomas Rösch ,[12] Cesare Hassan [3]

-AI group showed a significant increase in adenoma detection rate (53.3% vs. 44.5%, *RR 1.22 (1.04-1.40), P*=0.02)

Repici A, Spadaccini M, Antonelli G, et al. Artificial intelligence and colonoscopy experience: lessons from two randomised trials. Gut. 2022 Apr;71(4):757-765. doi: 10.1136/gutjnl-2021-324471. Epub 2021 Jun 29. PMID: 34187845.

Computers can help clinicians look at images

European Radiology (2022) 32:213–222
https://doi.org/10.1007/s00330-021-08162-8

CHEST

Check for updates

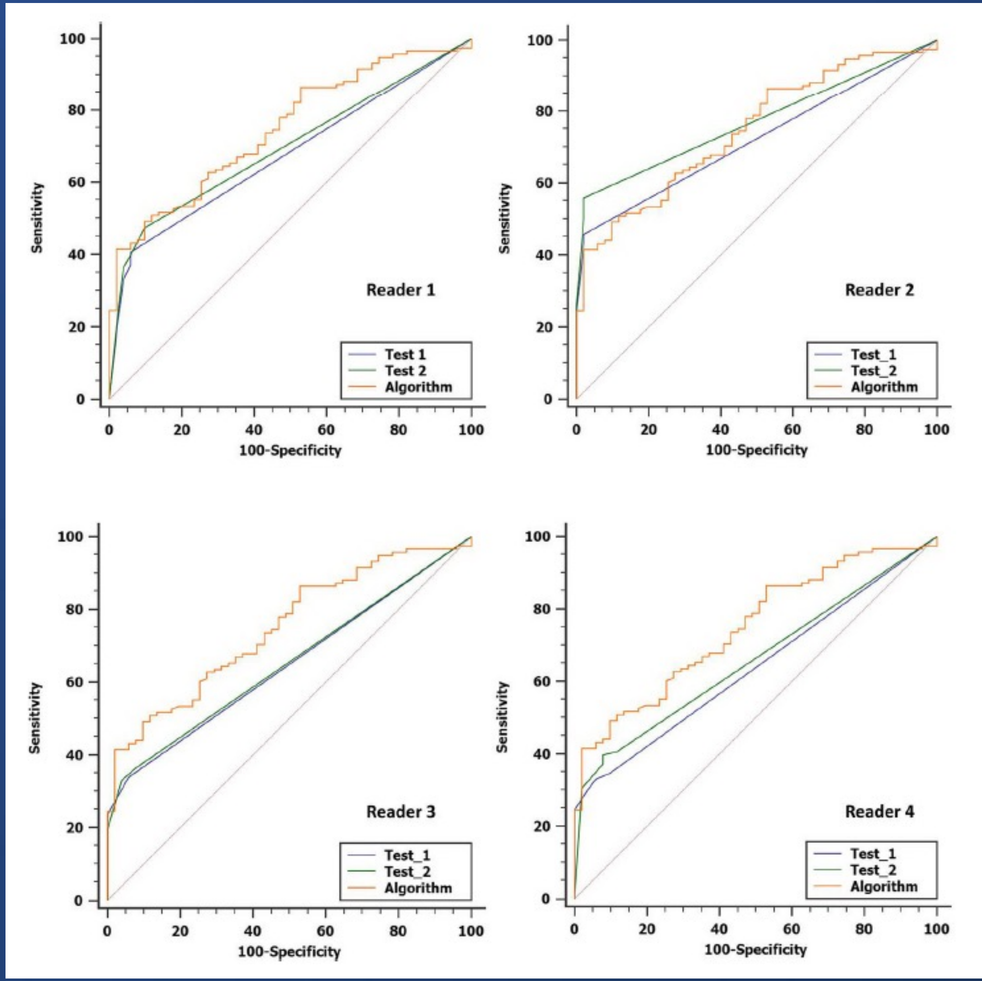
Value of a deep learning-based algorithm for detecting Lung-RADS category 4 nodules on chest radiographs in a health checkup population: estimation of the sample size for a randomized controlled trial

Ju Gang Nam[1] · Hyun Jin Kim[2] · Eun Hee Lee[3] · Wonju Hong[1] · Jongsoo Park[1] · Eui Jin Hwang[1] · Chang Min Park[1,4] · Jin Mo Goo[1,4,5]

-Used a previously developed commercial Neural Network AI[2]
-~3000 patients had a routine CXR and a CT chest
-Radiologist plus AI vs. Radiologist alone
-AI group showed better sensitivity (45.1% vs. 38.8%, $P<0.001$)
-Specificity unchanged (92.2% vs. 94.1%, $P=0.22$)
-AUC improved

1 Nam JG, Kim HJ, Lee EH, et al. Value of a deep learning-based algorithm for detecting Lung-RADS category 4 nodules on chest radiographs in a health checkup population: estimation of the sample size for a randomized controlled trial. Eur Radiol. 2022 Jan;32(1):213-222. doi: 10.1007/s00330-021-08162-8. Epub 2021 Jul 15. PMID: 34264351
2 Hwang EJ, Park S, Jin KN, et al. DLAD Development and Evaluation Group. Development and Validation of a Deep Learning-Based Automated Detection Algorithm for Major Thoracic Diseases on Chest Radiographs. JAMA Netw Open. 2019 Mar 1;2(3):e191095. doi: 10.1001/jamanetworkopen.2019.1095. Erratum in: JAMA Netw Open. 2019 Apr 5;2(4):e193260. PMID: 30901052

Computers can help clinicians look at images

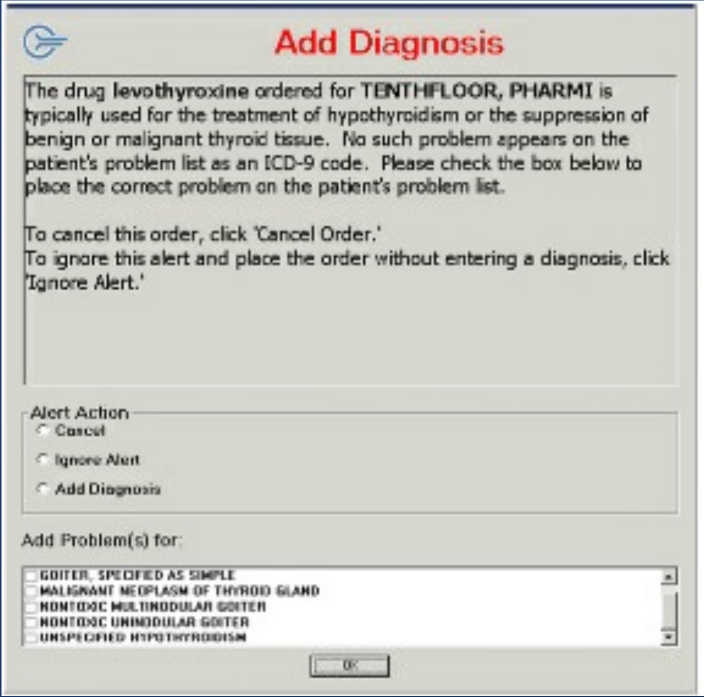


Radiologist + AI slightly better than radiologists alone, 0.70 vs. 0.67, P< 0.002

1 Nam JG, Kim HJ, Lee EH, et al. Value of a deep learning-based algorithm for detecting Lung-RADS category 4 nodules on chest radiographs in a health checkup population: estimation of the sample size for a randomized controlled trial. Eur Radiol. 2022 Jan;32(1):213-222. doi: 10.1007/s00330-021-08162-8. Epub 2021 Jul 15. PMID: 34264351

Self Promotion & the slow path of research

2002 -3 colleagues have an idea to modify their EHR (Galanter, Hier, Jao)
-Why not look at the problem list when ordering a med and suggest a problem when needed? We asked the vendor to modify the EHR.



2005 -the vendor was able to produce the modification

2007 -the modification actually worked

2010 *-the alerts can improve the problem list*[1]

2010 -this probably prevents errors. We need a grant!

2013 *-the alerts can intercept wrong patient errors*[2]

2014 *-the alerts can intercept drug name confusion errors*[3]

2015 -Do they work in another EHR? We need a grant!

1 Galanter WL, Hier DB, Jao C, Sarne D. Computerized physician order entry of medications and clinical decision support can improve problem list documentation compliance. Int J Med Inform. 2010 May;79(5):332-8. doi: 10.1016/j.ijmedinf.2008.05.005. Epub 2008 Jul 2. PMID: 18599342.
2 Galanter W, Falck S, Burns M, Laragh M, Lambert BL. Indication-based prescribing prevents wrong-patient medication errors in computerized provider order entry (CPOE). J Am Med Inform Assoc. 2013 May 1;20(3):477-81. doi: 10.1136/amiajnl-2012-001555. Epub 2013 Feb 9. PMID: 23396543
3 Galanter WL, Bryson ML, Falck S, et al. Indication alerts intercept drug name confusion errors during computerized entry of medication orders. PLoS One. 2014 Jul 15;9(7):e101977. doi: 10.1371/journal.pone.0101977. PMID: 25025346

Indication alerts in med CPOE; Epic & Allscripts

Journal of the American Medical Informatics Association, 29(5), 2022, 909–917
https://doi.org/10.1093/jamia/ocab285
Advance Access Publication Date: 27 December 2021
Research and Applications

Research and Applications

Indication alerts to improve problem list documentation

Anne Grauer[1], Jerard Kneifati-Hayek[1], Brian Reuland[1], Jo R. Applebaum[2], Jason S. Adelman[1,2], Robert A. Green[1,2], Jeanette Lisak-Phillips[1], David Liebovitz[3], Thomas F. Byrd IV[3], Preeti Kansal[3], Cheryl Wilkes[3], Suzanne Falck[4], Connie Larson[5], John Shilka[5], Elizabeth VanDril[5], Gordon D. Schiff[6], William L. Galanter[4,5,7], and Bruce L. Lambert[8]

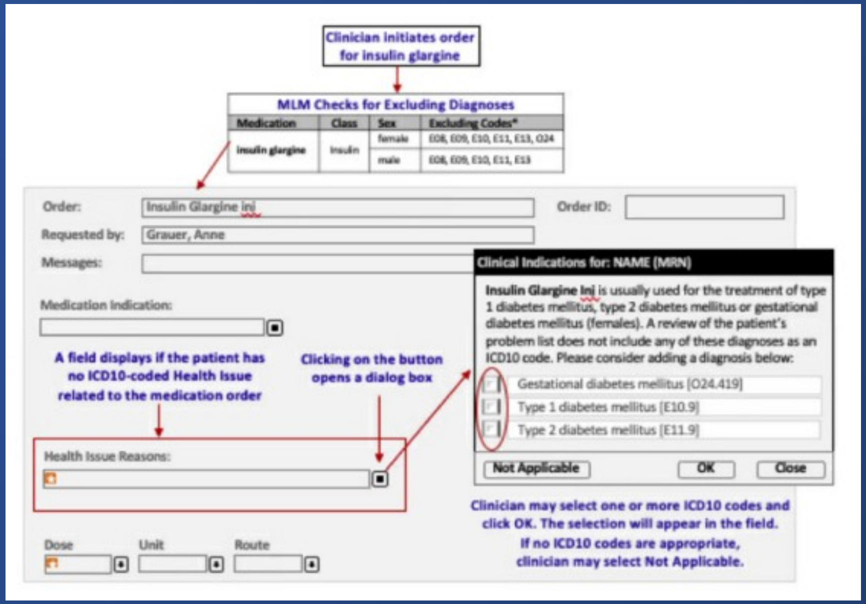
-A trial of indication alerts during medication CPOE at 2 large health systems

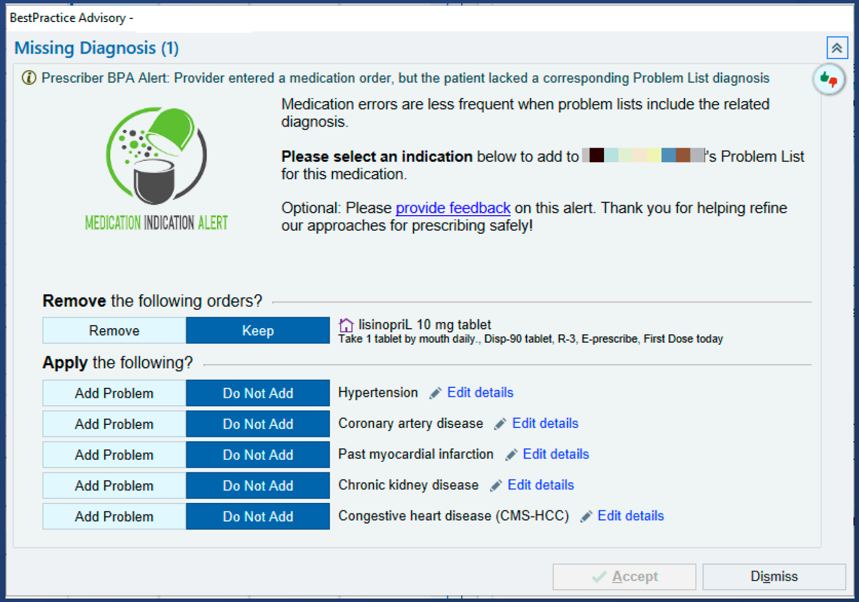
- -Northwestern Medicine using Epic
- -New York Presbyterian using Allscripts

-Each site was able to accept, reject or modify the clinical indication/medication logic from the original indication alerts site, UIC

Grauer A, Kneifati-Hayek J, Reuland B, Applebaum JR, Adelman JS, Green RA, Lisak-Phillips J, Liebovitz D, Byrd tF, Kansal P, Wilkes C, Falck S, Larson C, Shilka J, VanDril E, Schiff GD, Galanter WL, Lambert BL. Indication alerts to improve problem list documentation. J Am Med Inform Assoc. 2022 Apr 13;29(5):909-917. doi: 10.1093/jamia/ocab285. PMID: 34957491

Indication alerts in med CPOE; Epic & Allscripts





With Permission from Epic Corp.

-Yield at NYP was 109,005 problems documented from 131,134 orders or 83%

-Yield at NM was 2874 problems from 6178 orders or 46%.

Refills did not engage the CDS, thus much lower N

-Problem accuracy was 90 ± 2 %

-A surprisingly high number of medication orders were abandoned (never completed) after alert display, 11.1% and 9.6% at the 2 sites.

Grauer A, Kneifati-Hayek J, Reuland B, Applebaum JR, Adelman JS, Green RA, Lisak-Phillips J, Liebovitz D, Byrd tF, Kansal P, Wilkes C, Falck S, Larson C, Shilka J, VanDril E, Schiff GD, Galanter WL, Lambert BL. Indication alerts to improve problem list documentation. J Am Med Inform Assoc. 2022 Apr 13;29(5):909-917. doi: 10.1093/jamia/ocab285. PMID: 34957491

Example of a telerehab for a common problem

ORIGINAL RESEARCH — Annals of Internal Medicine

Comparing Video-Based, Telehealth-Delivered Exercise and Weight Loss Programs With Online Education on Outcomes of Knee Osteoarthritis

A Randomized Trial

Kim L. Bennell, PhD; Belinda J. Lawford, PhD; Catherine Keating, PhD; Courtney Brown, BHlthSc, BBus(Mktg); Jessica Kasza, PhD; Dave Mackenzie, MSc; Ben Metcalf, BSc; Alexander J. Kimp, DPT; Thorlene Egerton, PhD; Libby Spiers, BPhysio; Joseph Proietto, PhD; Priya Sumithran, PhD; Anthony Harris, MSc; Jonathan G. Quicke, PhD; and Rana S. Hinman, PhD

-Australian
-Knee DJD & BMI 28-40
-Information on the Web versus
    -Telerehab WITH Fitbit & bands
    -Telerehab and Telenutrition

Bennell KL, Lawford BJ, Keating C, et al. Comparing Video-Based, Telehealth-Delivered Exercise and Weight Loss Programs With Online Education on Outcomes of Knee Osteoarthritis : A Randomized Trial. Ann Intern Med. 2022 Feb;175(2):198-209. doi: 10.7326/M21-2388. Epub 2021 Nov 30. PMID: 34843383

Example of a telerehab for a common problem

Table 3. Change in Outcome Measures Within and Between Groups Over Time for Continuous Outcomes Using Multiply Imputed Data*

Outcome Measure	Mean Within-Group Change: Final Minus Baseline (SD)			Difference in Change Between Groups					
	Control	Exercise	Diet and Exercise	Exercise vs. Control		Diet and Exercise vs. Control		Diet and Exercise vs. Exercise	
				Mean (95% CI)	*P* Value	Mean (95% CI)	*P* Value	Mean (95% CI)	*P* Value
Change from baseline to 12 mo									
Primary outcomes									
Average overall knee pain (NRS)†‡	−1.7 (2.4)	−2.5 (2.4)	−3.1 (2.2)	−0.7 (−1.4 to −0.1)	0.028	−1.3 (−2.0 to −0.7)	<0.001	−0.6 (−1.0 to −0.1)	0.010
Physical function (WOMAC)†§	−4.8 (10.9)	−9.3 (9.8)	−13.0 (10.1)	−4.4 (−7.4 to −1.4)	0.004	−7.5 (−10.4 to −4.5)	<0.001	−3.1 (−5.1 to −1.1)	0.003
Secondary outcomes									
Body weight, kg†‖	−0.2 (6.3)	−2.2 (5.4)	−8.4 (7.3)	−2.1 (−3.9 to −0.3)	0.024	−8.4 (−10.2 to −6.5)	<0.001	−6.3 (−7.6 to −5.0)	<0.001

Bennell KL, Lawford BJ, Keating C, et al. Comparing Video-Based, Telehealth-Delivered Exercise and Weight Loss Programs With Online Education on Outcomes of Knee Osteoarthritis : A Randomized Trial. Ann Intern Med. 2022 Feb;175(2):198-209. doi: 10.7326/M21-2388. Epub 2021 Nov 30. PMID: 34843383

The common mixture of tele- and m- health intervention for a very common problem

Original Investigation | Psychiatry

Effect of Computer-Assisted Cognitive Behavior Therapy vs Usual Care on Depression Among Adults in Primary Care

A Randomized Clinical Trial

Jesse H. Wright, MD, PhD; Jesse Owen, PhD; Tracy D. Eells, PhD; Becky Antle, PhD; Laura B. Bishop, MD; Renee Girdler, MD; Lesley M. Harris, PhD; R. Brent Wright, MD; Michael J. Wells, MD; Rangaraj Gopalraj, MD; Michael E. Pendleton, MD; Shehzad Ali, PhD

-Commercial web-based CBT AND televisits AND text/email (n=94) vs. Routine Care (n=80)

-10% of patient were loaned a laptop and given internet access in treatment group

Wright JH, Owen J, Eells TD, et al. Effect of Computer-Assisted Cognitive Behavior Therapy vs Usual Care on Depression Among Adults in Primary Care: A Randomized Clinical Trial. JAMA Netw Open. 2022 Feb 1;5(2):e2146716. doi: 10.1001/jamanetworkopen.2021.46716. PMID: 35142833

The common mixture of tele- and m- health intervention for a very common problem

Table 2. CCBT vs TAU: Intention-to-Treat Effect Sizes and Mean Ratings for Outcome Measures

		12 wk				3-mo Follow-up				6-mo Follow-up			
Group	Baseline	Mean score (95% CI)	Mean difference	Cohen *d*	*P* value	Mean score (95% CI)	Mean difference	Cohen *d*	*P* value	Mean score (95% CI)	Mean difference	Cohen *d*	*P* value
PHQ-9													
CCBT	16.1 (14.9 to 17.3)	8.6 (7.4 to 9.8)	−2.5	−0.46	.005	8.8 (7.3 to 10.2)	−2.3	−0.38	.006	9.4 (7.9 to 10.9)	−3.2	−0.52	.01
TAU	16.2 (14.9 to 17.6)	11.1 (9.6 to 12.6)				11.1 (9.7 to 12.4)				12.6 (10.8 to 14.4)			
ATQ													
CCBT	87.9 (81.8 to 94.1)	65.8 (59.3 to 72.4)	−13.5	−0.46	.009	67.6 (60.6 to 74.6)	−8.4	−0.29	.01	69.1 (61.9 to 76.3)	−10.3	−0.35	.04
TAU	86.7 (80.7 to 92.6)	79.3 (73.2 to 85.5)				76.0 (69.0 to 83.0)				79.4 (71.8 to 86.9)			
GAD-7													
CCBT	12.3 (11.1 to 13.5)	7.1 (5.9 to 8.3)	−2.8	−0.47	.005	8.0 (6.6 to 9.8)	−1.9	−0.32	.002	8.3 (6.8 to 9.8)	−1.6	−0.28	.23
TAU	12.4 (11.2 to 13.7)	9.9 (8.6 to 11.2)				9.9 (8.9 to 11.7)				9.9 (8.2 to 11.7)			
SWLS													
CCBT	14.2 (13.0 to 15.5)	17.9 (16.7 to 19.0)	3.3	0.49	.007	18.3 (16.9 to 19.7)	2.6	0.39	.003	17.7 (16.2 to 19.3)	2.9	0.43	.02
TAU	13.4 (11.9 to 14.7)	14.6 (12.7 to 16.5)				15.7 (13.9 to 17.4)				14.8 (13.0 to 16.5)			

Abbreviations: ATQ, Automatic Thoughts Questionnaire; CCBT, computer-assisted cognitive behavior therapy; GAD-7, Generalized Anxiety Disorder-7; PHQ-9, Patient Health Questionnaire-9; SWLS, Satisfaction With Life Scale; TAU, treatment as usual.

Wright JH, Owen J, Eells TD, et al. Effect of Computer-Assisted Cognitive Behavior Therapy vs Usual Care on Depression Among Adults in Primary Care: A Randomized Clinical Trial. JAMA Netw Open. 2022 Feb 1;5(2):e2146716. doi: 10.1001/jamanetworkopen.2021.46716. PMID: 35142833

In light of the ongoing contrast shortage….

Canadian Journal of Emergency Medicine (2021) 23:631–640
https://doi.org/10.1007/s43678-021-00170-3

ORIGINAL RESEARCH

Check for updates

Decision support for computed tomography in the emergency department: a multicenter cluster-randomized controlled trial

James E. Andruchow[1,3] · Daniel Grigat[2] · Andrew D. McRae[1,3] · Grant Innes[1,3] · Shabnam Vatanpour[1] · Dongmei Wang[1] · Monica Taljaard[4,5] · Eddy Lang[1,3]

-Prior to the contrast shortage

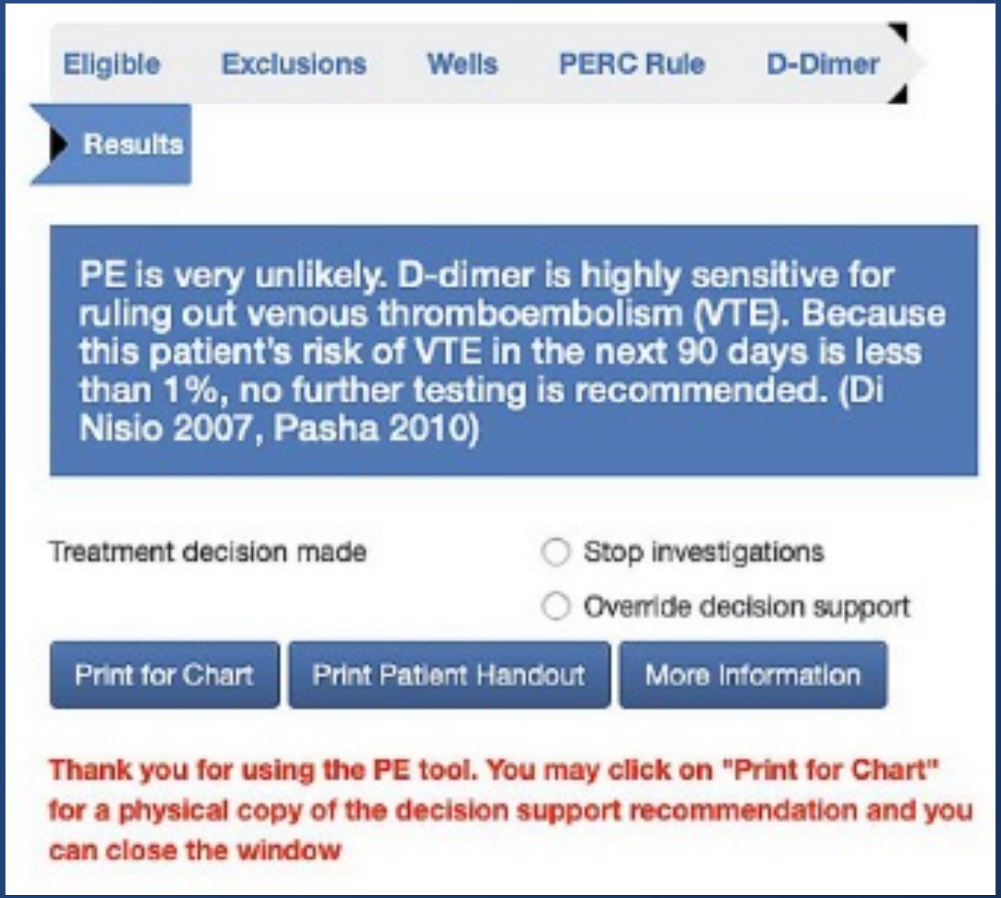
-RCT Canadian urban ED's, volunteer consented subjects

-CDS for evidenced based ordering of non-contrast CT's for head injuries and contrast CT's for suspicion of pulmonary embolism

-Outcome was the # of studies ordered

Andruchow JE, Grigat D, McRae AD, Innes G, Vatanpour S, Wang D, Taljaard M, Lang E. Decision support for computed tomography in the emergency department: a multicenter cluster-randomized controlled trial. CJEM. 2021 Sep;23(5):631-640. doi: 10.1007/s43678-021-00170-3. Epub 2021 Aug 5. PMID: 34351598

In light of the ongoing contrast shortage….



Andruchow JE, Grigat D, McRae AD, Innes G, Vatanpour S, Wang D, Taljaard M, Lang E. Decision support for computed tomography in the emergency department: a multicenter cluster-randomized controlled trial. CJEM. 2021 Sep;23(5):631-640. doi: 10.1007/s43678-021-00170-3. Epub 2021 Aug 5. PMID: 34351598

In light of the ongoing contrast shortage….

Table 2 CT utilization and diagnostic yield by clinical scenario

		Baseline period (Aug 1, 2014–Aug 1, 2016)		Post-intervention period (Aug 2, 2016–Aug 30, 2017)			
Head injury cohort							
Randomization	Physicians *N*	Patient encounters *N*	Head CT Performed *N* (%)	Patient encounters *N*	Head CT Performed *N* (%)	Adjusted Odds Ratio (95% CI)	*p* value
CT head utilization, all ages							
Intervention	101	5136	2133 (41.5)	3085	1227 (39.8)	0.91 (0.74–1.08)	0.31
Control	103	4614	1979 (42.9)	2602	1112 (42.7)		
Total	204	9750	4112 (42.2)	5687	2339 (41.1)		
Suspected pulmonary embolism cohort							
Randomization	Physicians *N*	Patient encounters *N*	CT Performed *N* (%)	Patient encounters *N*	CT Performed *N* (%)	Adjusted Odds Ratio (95% CI)	*p* value
CT utilization							
Intervention	104	28,328	1790 (6.3)	15,330	947 (6.2)	0.98 (0.87, 1.11)	0.74
Control	101	29,891	1947 (6.5)	16,814	1048 (6.2)		
Total	205	58,219	3737 (6.4)	32,144	1995 (6.2)		

Andruchow JE, Grigat D, McRae AD, Innes G, Vatanpour S, Wang D, Taljaard M, Lang E. Decision support for computed tomography in the emergency department: a multicenter cluster-randomized controlled trial. CJEM. 2021 Sep;23(5):631-640. doi: 10.1007/s43678-021-00170-3. Epub 2021 Aug 5. PMID: 34351598

What is the science behind result presentation?

Research and Applications

A visual representation of microbiological culture data improves comprehension: a randomized controlled trial

Eugene Y. Kim,[1,2] Anne V. Grossestreuer,[2] Charles Safran,[1] Larry A. Nathanson,[1,2] and Steven Horng[1,2,3]

-Unblinded RCT
-A single ED
-Home grown EHR
-After antibiotic prescribing in patients with prior sensitivities an RA did a survey
-~1/2 of the clinician received the new view and ~1/2 the old view

Kim EY, Grossestreuer AV, Safran C, Nathanson LA, Horng S. A visual representation of microbiological culture data improves comprehension: a randomized controlled trial. J Am Med Inform Assoc. 2021 Aug 13;28(9):1826-1833. doi: 10.1093/jamia/ocab056. PMID: 34100952

What is the science behind result presentation?

Date drawn ↑↓	Source ↑↓	Organism ↑↓	PENICILLIN G	AMPICILLIN	OXACILLIN	CEFAZOLIN	CEFTAZIDIME	CEFTRIAXONE	CEFEPIME	AMPICILLIN/SULBACTAM	PIPERACILLIN/TAZO	MEROPENEM	LINEZOLID	VANCOMYCIN	CLINDAMYCIN	TRIMETHOPRIM/SULFA	NITROFURANTOIN	CIPROFLOXACIN	LEVOFLOXACIN	GENTAMICIN	TOBRAMYCIN	ERYTHROMYCIN	TETRACYCLINE	DAPTOMYCIN
03/22/27	URINE	ESCHERICHIA COLI		I		S	S	S	S	I	S	S				S	S	R		S	S			
01/08/27	URINE	ESCHERICHIA COLI				S	S	S	S	S	S	S				S	S	R		S	S			
01/08/27	URINE	ENTEROCOCCUS SP.		S										S			S						R	
10/23/26	URINE	ESCHERICHIA COLI		R		R	R	R	R	R		S				S	S	R		S	S			
10/23/26	URINE	KLEBSIELLA OXYTOCA				R	S	S	S	R	S	S				S	S	S		S	S			
08/14/26	URINE	KLEBSIELLA PNEUMONIAE				S	S	S	S	S	S	S				S	I	S		S	S			
08/11/26	URINE	KLEBSIELLA PNEUMONIAE				S	S	S	S	S	S	S				S	I	S		S	S			
07/28/26	URINE	ENTEROCOCCUS SP.																						
07/25/26	URINE	ESCHERICHIA COLI		R		R	R	R	R	R	S	S				S	S	R		S	R			
07/25/26	URINE	ENTEROCOCCUS SP.		S									S	R			S						R	
07/22/26	URINE	ESCHERICHIA COLI		R		R	R	R	R	R		S				S	S	R		S	R			
07/21/26	URINE	KLEBSIELLA PNEUMONIAE				S	S	S	S	S	S	S				S	S	S		S	S			
07/21/26	URINE	STENOTROPHOMONAS MALTOPHILIA														S								
07/04/26	URINE	ENTEROCOCCUS SP.		S									S	R			S						S	

Figure 1. Screen capture of visualization tool.

Kim EY, Grossestreuer AV, Safran C, Nathanson LA, Horng S. A visual representation of microbiological culture data improves comprehension: a randomized controlled trial. J Am Med Inform Assoc. 2021 Aug 13;28(9):1826-1833. doi: 10.1093/jamia/ocab056. PMID: 34100952

What is the science behind result presentation?

Table 2. Cohen's kappa for agreement between provider responses and patients' previous microbiological culture data

	Kappa
Overall kappa between provider and EHR (n = 3036)	0.42 (0.39–0.43)
Control (n = 1458)	0.16 (0.12–0.20)
Intervention (n = 1578)	0.69 (0.65–0.73)

Table 4. Secondary outcomes assessing changes in antibiotic orders and resistance to antibiotics administered in the ED

	Control	Intervention	*P* value
ED antibiotics did not adequately treat infection[a] (n = 64), number (%)	5 (16)	6 (18)	>0.999

Kim EY, Grossestreuer AV, Safran C, Nathanson LA, Horng S. A visual representation of microbiological culture data improves comprehension: a randomized controlled trial. J Am Med Inform Assoc. 2021 Aug 13;28(9):1826-1833. doi: 10.1093/jamia/ocab056. PMID: 34100952

Transition Comedy Slide: Regulatory and More

Original Investigation | Health Informatics

Association of Hospital Public Quality Reporting With Electronic Health Record Medication Safety Performance

A. Jay Holmgren, PhD, MHI; David W. Bates, MD, MSc

JAMA Network Open

The premise:

EHRs still haven't delivered on large scale safety promises

- Does public reporting improve performance ?
- Analyze all of the Leapfrog CPOE data from 2017 (~1200 hospitals) to see if hospitals who had negative feedback that was publicly reported improved more than those who didn't ?
- Is the improvement in the realm of basic or advanced CDS ?

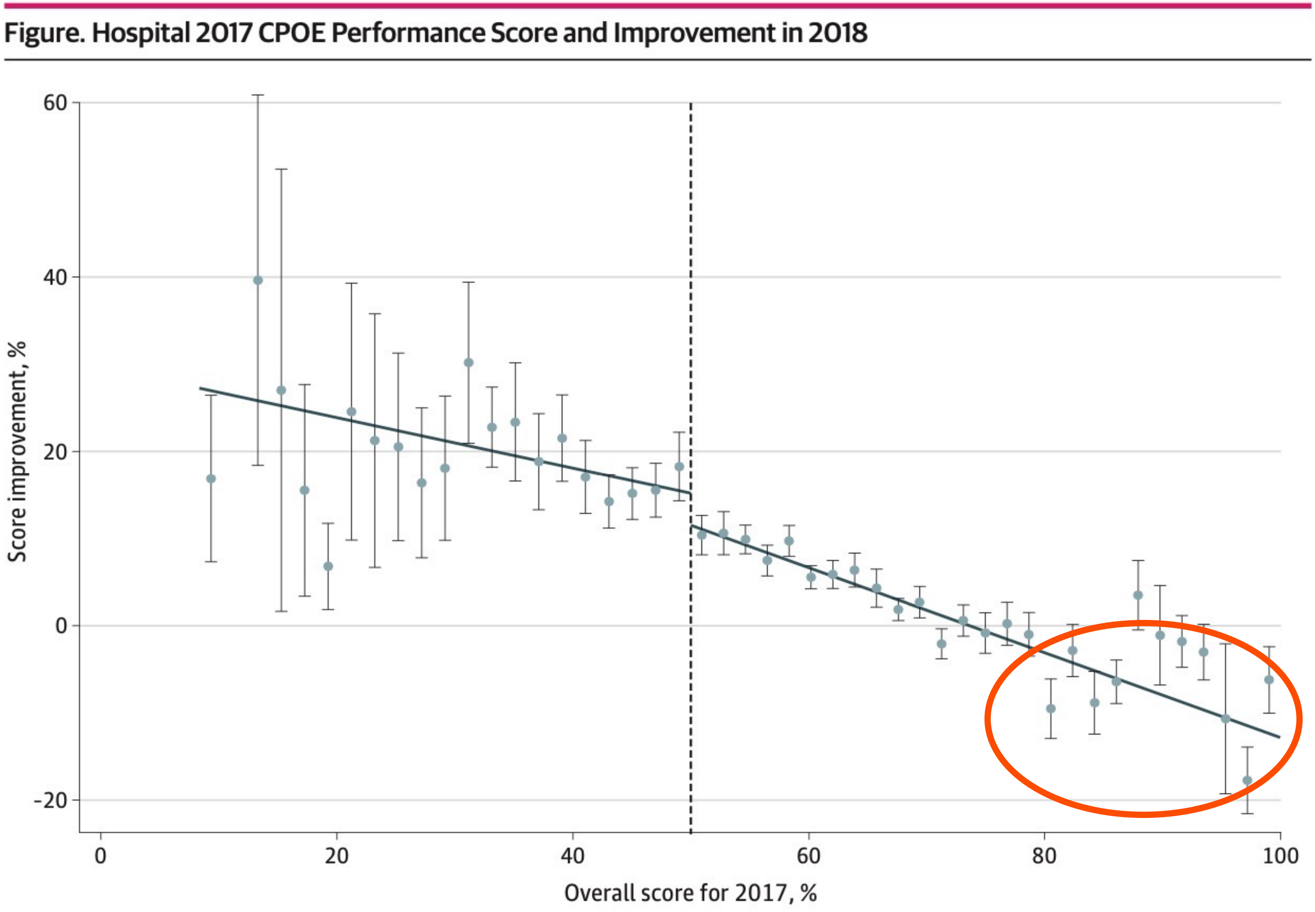
1) Full demonstration of safety measures at scores >50%

2) Partial demonstration of safety measures at 30-49%

3) Some demonstration of safety measures at < 30 %

So how did groups 2 and 3 do on the eval in 2018?

LEAPFROG HOSPITAL SURVEY



?

WISKEY
TANGO
FOXTROT

Leapfrog Shaming ?

Yes – poor scores equals bigger improvement the next year

The improvements are in the realm of "basic CDS"

- Drug / Drug
- Drug / Allergy

Not "advanced CDS"

- Daily dosing contraindications
- Corollary orders

LEAPFROG HOSPITAL SURVEY

Limitations

- Self selection for taking the test
- Could only use 2 years of data based on changes in the scoring
- There are decision support modalities that are not part of the test (think ordersets / dashboards / etc)
- Yes – good Leapfrog score is associated with better safety outcomes but it hasn't been studied in 10 years

<u>My cynical view - or did you just get better at taking / gaming the simulation?</u>

PUBLIC HEALTH

Tennessee nurse convicted in lethal drug error sentenced to three years probation

May 13, 2022 · 4:50 PM ET

- RaDonda Vaught - Neuro-ICU helper nurse (not primary)
- Roadshow for PET scan
- 1mg Versed ordered for anxiety
- 2 letter search “V-E” yields no hit on the dispensing cabinet
- Override
- She inputs override reasons given in dispense
- 3 screens of “WARNING PARALYZING AGENT” also on the bottle itself (the cap)
- Vecuronium powder needs to be re-constituted (Versed does not)
- Given to patient – left un-monitored for 30min
- Anoxic brain injury – withdrawal of care
- Some failure to report / anonymous tipster
- Criminal Charges – Guilty of Criminally negligent homicide

The Full Timeline - https://www.freshrn.com/radonda-vaught-trial/#:~:text=On%20March%2025%2C%202022%20after,sentences%20will%20likely%20run%20concurrently.

5 letter search on dispensing cabinets

Letters typed	Intended drug (effect)	Withdrawn drug (effect)	Year of error report
V-E	Versed (sedative)	vecuronium (paralytic)	2017
V or V-E*	Versed (sedative)	vecuronium (paralytic)	2019
K-E-T	ketamine (aids in anesthesia)	ketorolac (pain reliever)	2019
R-O	rocuronium (paralytic)	Romazicon (reverses sedatives, overdoses)	2019
R or R-O*	rocuronium (paralytic)	Romazicon (reverses sedatives, overdoses)	2021
R-O	rocuronium (paralytic)	Rocephin (antibiotic)	2021
P-I-T	Pitocin (induces labor)	Pitressin (treats diabetes insipidus)	2021
V-E-R	Versed (sedative)	verapamil (treats high blood pressure, chest pain)	2022

https://khn.org/news/article/medication-cabinet-hospital-drug-errors/

The End