# Coaching Session In-progress

Please come in and find your table but keep noise to a minimum.

Thanks!

# DHA Antimicrobial Stewardship: Intervention Plan

Aim Statement

- Inputs (1-2 liner about findings from each that influenced your intervention)
  - Voice of the customer
  - Affinity diagram/Process Map
  - Pre-mortem
- Proposed Intervention

# Certificate Training Program Session 15

#### Welcome! Before We Begin:

Sign-in at the back
Pick up agenda
Sit with your CTP team at your assigned table

SCHOOL OF MEDICINE

UNIVERSITY OF COLORADO ANSCHUTZ MEDICAL CAMPUS

#### **CALL FOR APPLICATIONS**

### CERTIFICATE TRAINING PROGRAM (CTP)

#### Learn | Develop | Lead

A professional development program for inter-professional leadership teams of outpatient clinics, hospital units, or multi-site clinical programs.

- Yearlong course combining classroom sessions, coaching, and completion of a process improvement project
- Focus on leadership, change management, team development, patient safety, quality and process improvement

Application & letters of support due April 14, 2025

### CLINICAL EFFECTIVENESS & PATIENT SAFETY (CEPS) GRANT

#### **Seeding Promising Ideas**

Providing funding to faculty, staff, and trainees up to \$25,000 for initiatives at CHCO or UCH with a focus on:

- Innovative process improvements
- Patient safety outcomes
- Increasing healthcare value
- Implementing evidence-based practices

**Letter of Intent due April 14, 2025** 



Need help building your strongest application?
Contact us! IHQSE@cuanschutz.edu

Visit ihqse.org for more information





### We are hiring!

- Education and Events Program Manager
- New role within the IHQSE leadership team
  - Manage and grow our portfolio of programs
  - o Ensure we are delivering a premium experience for all attendees
  - Improve program evaluation
- Please share! We will include link to job posting in follow-up email

| KEY            |  |  |  |  |  |
|----------------|--|--|--|--|--|
| Team Check-in  |  |  |  |  |  |
| Inspiration    |  |  |  |  |  |
| Background     |  |  |  |  |  |
| Process        |  |  |  |  |  |
| Improvement    |  |  |  |  |  |
| Leadership     |  |  |  |  |  |
| Quality/Safety |  |  |  |  |  |
| Coaching       |  |  |  |  |  |
| EMR            |  |  |  |  |  |

| KEY  | Team ( | Check-in Inspiration                | on Background                              | Process In                           | nprovement                           | Leadership                | Quality/Safet                      | ty Coaching         |  |
|------|--------|-------------------------------------|--|--------------------------------------|--------------------------------------|---------------------------|------------------------------------|---------------------|--|
| 1/28 | #12    | UCH Sleep                           | Overcoming<br>Resistance                   | Feedback to                          | back to Improve Performance          |                           | Mid-year Repo                      | rt Practice Session |  |
| 2/4  |        |                                     | Coaching                                   |                                      |                                      |                           |                                    |                     |  |
| 2/11 | #13    |                                     | Repor                                      |                                      | Leading Change:<br>Removing Barriers |                           |                                    |                     |  |
| 2/18 |        | Coaching                            |  |                                      |                                      |                           |                                    |                     |  |
| 2/25 | #14    |                                     | Repor                                      | t Outs                               |                                      |                           | Running Effective Meetings         |                     |  |
| 3/4  |        | Coaching                            |  |                                      |                                      |                           |                                    |                     |  |
| 3/11 | #15    | Using Al                            | for QI                                     | Leadership Journey: Jena<br>Hausmann |                                      |                           | Second Victim                      |                     |  |
| 3/18 |        | Coaching                            |  |                                      |                                      |                           |                                    |                     |  |
| 3/25 |        |                                     | Coaching                                   |                                      |                                      |                           |                                    |                     |  |
| 4/1  | #16    | DHA Antimicrobial<br>Stewardship    | Data to<br>Understand<br>Impact            | Positive Organizational Design       |                                      | sign                      | Leading Change:<br>Short-term Wins |                     |  |
| 4/8  | #17    | CU Medicine<br>Dermatology          | Impact of Quality (<br>Healthcare I        |                                      |                                      | _                         | DEI & Leadership                   |                     |  |
| 4/15 |        |                                     |  | Coaching                             |                                      |                           |                                    |                     |  |
| 4/22 | #18    | CHCO Nursery                        |  | Strategic Planning                   |                                      |                           | QI Spread                          | Power & Influence   |  |
| 4/29 |        |                                     |  | Coaching                             |                                      |                           |                                    |                     |  |
| 5/13 | #19    | UCH Infectious<br>Diseases          | Burnout & Resilience Innovation in Healtho |                                      |                                      | Healthcare                | Embed the Change                   |                     |  |
| 5/20 |        |                                     | Coaching                                   |                                      |                                      |                           |                                    |                     |  |
| 5/27 | #20    | Leadership Journey:<br>Dean Sampson | Report Outs                                |                                      |                                      |                           |                                    |                     |  |
| 6/3  |        | Coaching                            |  |                                      |                                      |                           |                                    |                     |  |
| 6/10 | #21    | Report Outs                         |  |                                      |                                      |                           |                                    |                     |  |
| 6/17 |        | Coaching                            |  |                                      |                                      |                           |                                    |                     |  |
| 6/24 | #22    | Re                                  | eflecting on Why                           |                                      | Certi                                | Certificates Closing Time |                                    |                     |  |
|      |        |                                     |  |                                      |                                      |                           |                                    |                     |  |

| KEY            | Team Check-in                                | eam Check-in Inspiration Background Process Improvement |   |                                 | Leadership  | Qual   | lity/Safety | Coaching  |  |
|----------------|--|---|---|---------------------------------|-------------|--|-------------|---|--|
| Coaching       | Develop mid-year report out                  |   |   |                                 |             |  |             |   |  |
| #14<br>Feb. 25 | Report Outs                                  |   | How do I share my project work with others? |                                 |             | Create a plan for<br>removing barriers to<br>success<br>Due March 25 |             | <ul> <li>✓ Mid-year Report</li> <li>✓ Create a plan for removing barriers to success</li> </ul> |  |
|                | Running Effective Meetings                   |   | How can we run more effective meetings?     |                                 |             |  |             |   |  |
| Coaching       | Create plan for removing barriers to success |   |   |                                 |             |  |             |   |  |
| #15<br>Mar. 11 | Leadership Journey<br>Jena Hausmann          | :   | What does it take to suc<br>positions?      | cceed in progressive leadership |             |  |             |   |  |
|                | Second Victim                                |   | How should we act/read                      | ct when things go wrong?        |             |  |             |   |  |
|                | Using AI for QI                              |   | How will AI impact heal                     | thcare?                         |             |  |             |   |  |
| Coaching       | Finalize barrier removal                     |   |   |                                 |             |  |             |   |  |
| #16<br>Apr. 1  | Team Check-in: DHA<br>Antimicrobial Stewa    |   | Who are my colleagues                       | ?                               |             | Create a series of short-  |             |   |  |
|                | Data to Understand                           | l Impact  | How do I know if my pro<br>change?          | oject has made a significant    |             | term wins to support<br>project<br>Due April 8                       |             |   |  |
|                | Positive Organization                        | onal Design   | How do I build a high-pe                    | erforming culture?              | Due April o |  |             |   |  |

### Today's Learning Objectives

- 1 See an example of the leadership journey from a healthcare executive.
- 2 Recognize and support the care givers involved in safety events.
- 3 Understand current state of AI in healthcare.
- Understand some simple prompting techniques that can increase the effectiveness of large language models.
- 5 Recognize limitations in use of large language models in healthcare.



# HARNESSING AI IN OUR HEALTHCARE IMPROVEMENT JOURNEY

James Barry MD, MBA

Professor of Pediatrics, Section of Neonatology University of Colorado School of Medicine



Department of Pediatrics

SCHOOL OF MEDICINE

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### **Topics**

What is Artificial Intelligence (AI)? +

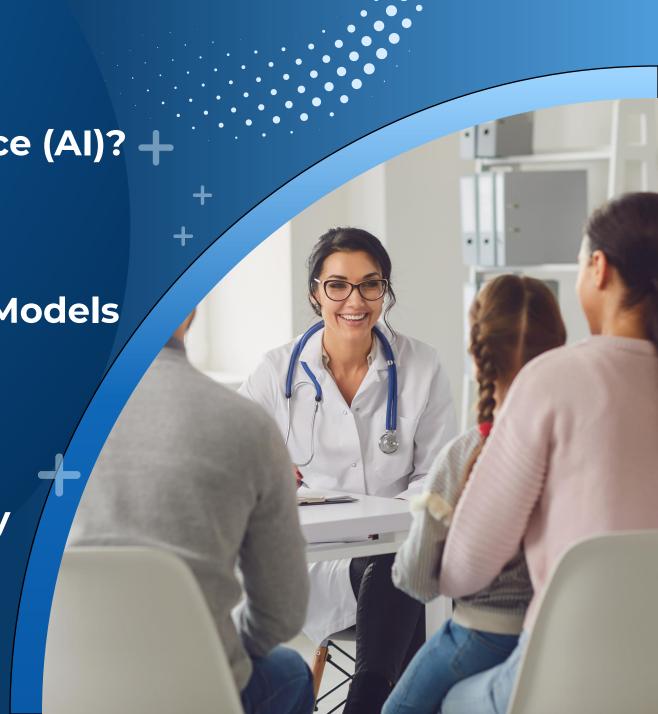
Where is AI in Healthcare?

 What are Large Language Models (LLMs)?

Pertinent Prompting

LLMs For Quality and Safety

Understanding LLM Bias



# Could AI Have Assisted Our IHQSE Project?

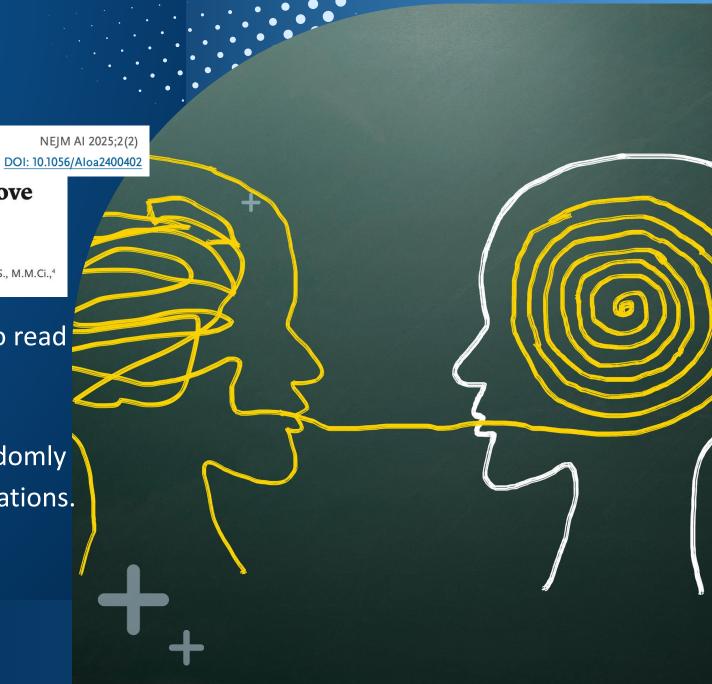
A Cross-Sectional Study of GPT-4-Based Plain

Language Translation of Clinical Notes to Improve
Patient Comprehension of Disease Course and
Management

Anivarya Kumar , B.A.,¹ Huanfei Wang , B.S.,² Kelly W. Muir , M.D., M.H.Sc.,³ Vishala Mishra , M.B.B.S., M.M.Ci.,⁴ and Matthew Engelhard , M.D., Ph.D.⁵

-553 pts; Dec 2023 - Feb 2024, >18 YOA, able to read English, no cognitive impairment

-read 4 DC summaries, 2 DSNs (selected at randomly replaced by GPT-4-based plain language translations.



## Could AI Have Assisted Our IHQSE Project?

A Cross-Sectional Study of GPT-4-Based Plain Language Translation of Clinical Notes to Improve Patient Comprehension of Disease Course and Management

Anivarya Kumar , B.A., Huanfei Wang , B.S., Kelly W. Muir , M.D., M.H.Sc., Vishala Mishra , M.B.B.S., M.M.Ci.

- -392 (72.73%) reported little-to-no health-related knowledge,
- -341 (63.27%) had a Bachelor's degree or lower
- -188 (34.88%) had a low-to-medium proficiency in English

-LLMs can be used to improve patients' understanding of clinical notes, including details clinical visits and steps for self-management of disease.

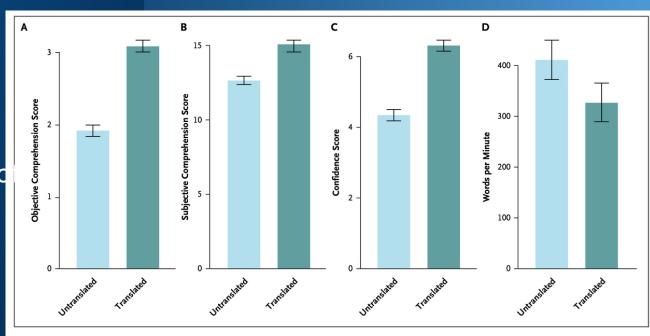


Figure 1. Effect of GPT-4-Translation on Objective and Subjective Comprehension, Confidence, and Reading Time across All Discharge Summary Notes.

#### Resources

#### AIMED: https://ai-med.io





Author: Anthony Chang, MD, MBA, MPH, MS

I am a pediatric cardiologist and have cared for children with heart disease for the past three decades. In addition, I have an educational background in business and finance as well as healthcare administration and global health – I gained a Masters Degree in Public Health from UCLA and taught Global Health there after I completed the program.

American Board of Al in Medicine (ABAIM). Multidisciplinary two-day introductory and advanced courses with educational certification as well as a one-day Al primer for everyone have been ongoing for almost two years.

The Alliance for Centers of Artificial Intelligence in Medicine (ACAIM) is a coalition of the centers around the world that have a dedicated leader and team within a health center with a focus on artificial intelligence in all dimensions of medicine and healthcare. We have now a total of over 50 centers, including more than 20 Al-focused efforts in pediatric health institutions.

**Medical Intelligence Society (MIS).** Clinicians and data scientists with interest and passion for AI in clinical medicine and healthcare with **monthly meeting** and **annual summit** in July. (MISociety.org)

#### Other Al Resources

#### **Books:**

- 1. "Artificial Intelligence: A Modern Approach" by Stuart Russell and Peter Norvig
- 2. "Deep Learning" by Ian Goodfellow, Yoshua Bengio, and Aaron Courville
- 3. "Artificial Intelligence with Python" by Prateek Joshi

#### Websites:

#### **Medical Journals:**



- 1. OpenAI (openai.com) 1.NEJMAI (https://ai.nejm.org)
- 2. AI Conference (aiconf.org) 2.JAMA+AI (https://jamanetwork.com/channels/ai)
- 3. AI-Forum (ai-forum.org)
- 4. Stanford Artificial Intelligence Laboratory (ai.stanford.edu)

#### **Online Courses:**

- 1. Coursera's Introduction to Artificial Intelligence (coursera.org/learn/introduction-to-ai)
- 2. Udacity's Artificial Intelligence Nanodegree (udacity.com/course/artificial-intelligence-nanodegree-nd898)
- 3. edX's Artificial Intelligence Fundamentals (edx.org/learn/artificial-intelligence)

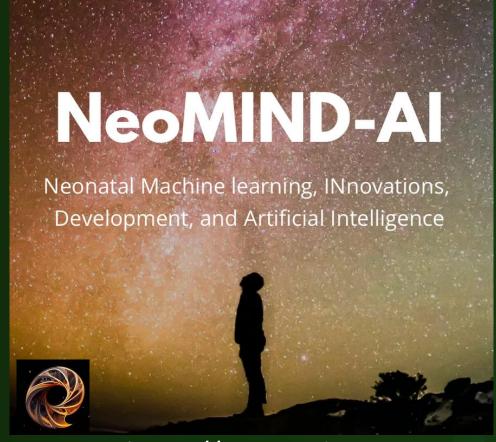
### About US

We have come together in the spirit of collaboration and curiosity

WHO?

Neonatologists, Data Scientists, and Clinical Informaticists

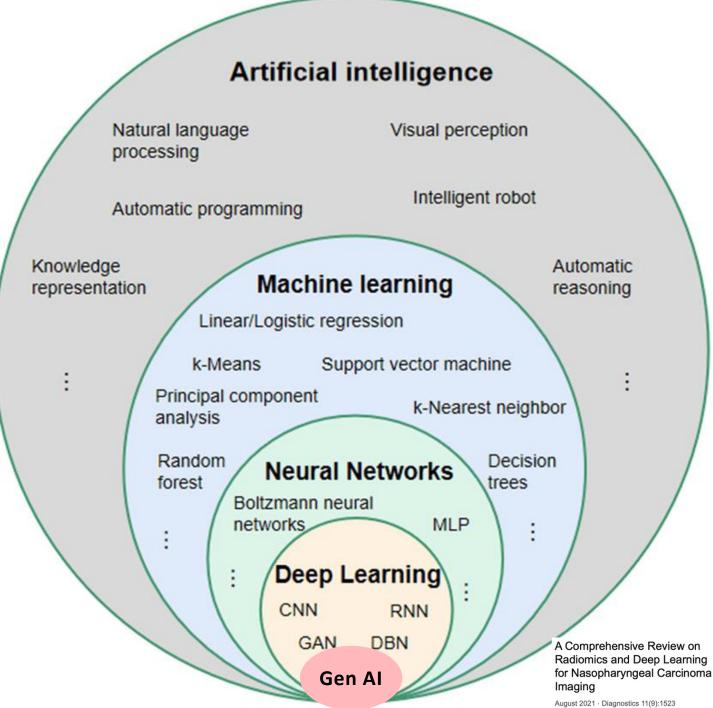
WHY?



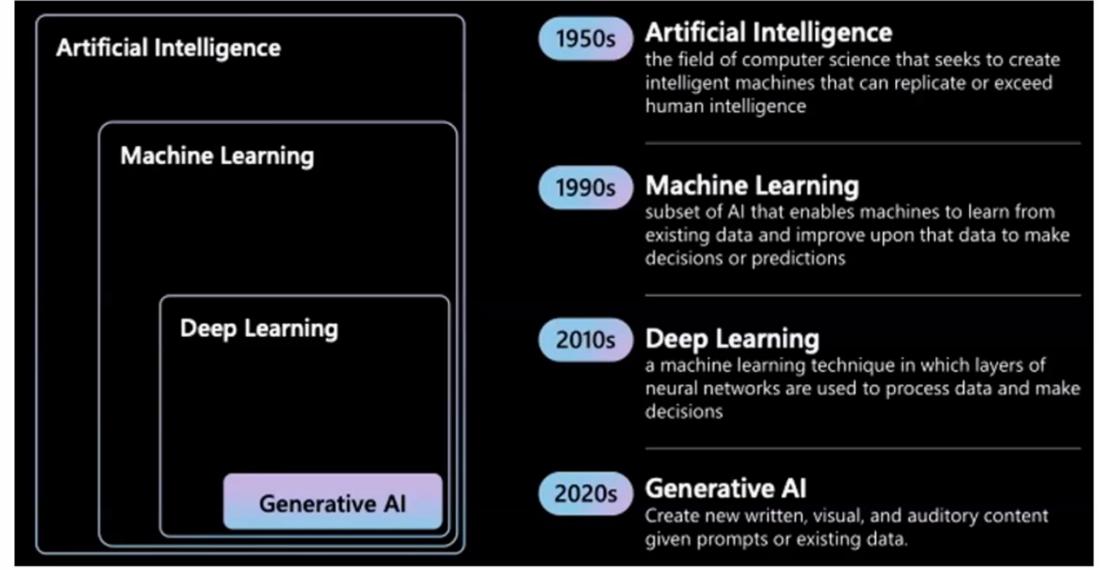
https://neomindai.com

Focus on AI; Neonatal and Pediatric Critical Care/Medicine





### Al is not new, but Generative Al is



Intelligence-Based Medicine, Anthony Chang, Elsevier 2020

### Al Based On Capabilities

#### **AI Realized today**

#### 1-Narrow

2-Artificial General Intelligence

- -Only type that exists Uses previously learned skills and
- today

learnings to accomplish a new task -Has a defined task without the need of human training--TRANSFER LEARNING

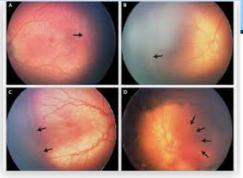
- -Needs a human to
- train it
- -Siri, self driving cars

- -can do anything that a human could do.
- -can do any cognitive task.
- -Self driving car that drives around a protest

**Theoretical AI** 

3-Super Al

- -would think, reason, learn, make judgements, and possess cognitive abilities that exceed humans.
- -would have own emotions, beliefs, and needs



Retinopathy of Prematurity | NEJM nejm.org

#### MACHINE LEARNING

#### **LABELED DATA**

SUPERVISED LEARNING

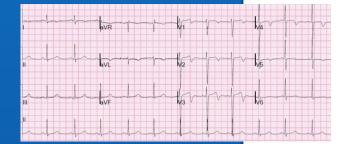
#### **UNLABELED DATA**

UNSUPERVISED LEARNING





**NEC** 



CLASSIFICATION

REGRESSION

CLUSTERING



Chang AC. Intelligence-Based Medicine: Principles and Applications of Artificial Intelligence and Human Cognition in Clinical Medicine and Healthcare (published by Elsevier 2020)

### NICU PHYSIOLOGICAL DATA

Reduction in Mortality by 20% with Neonatal Heart Rate Variability Changes Due to Sepsis--- HeRO Monitoring





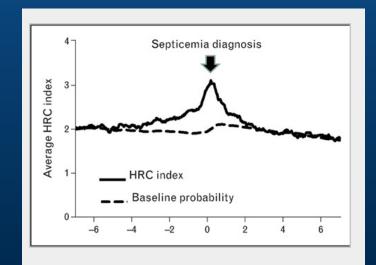
HeRO ES is an embedded HeRO System that can run within specific Philips Intellivue MX monitors!

### Predictive monitoring for early detection of sepsis in neonatal ICU patients

Fairchild, Karen D.

**Author Information ⊗** 

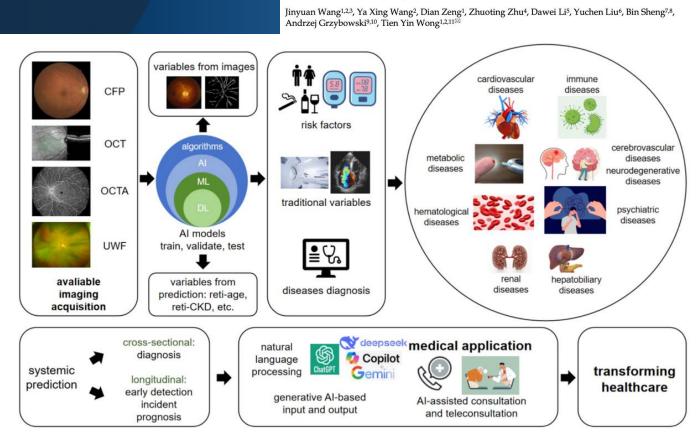
Current Opinion in Pediatrics 25(2):p 172-179, April 2013. | DOI: 10.1097/MOP.0b013e32835e8fe6



### ML and DL analysis of retinal images to detect

### pathology

- Age and Biological Age Estimation (e.g., "Retinal Age Gap")
- Gender Identification
- Body Mass Index (BMI)
- Smoking Status
- Hemoglobin A1c (HbA1c) levels
- Blood Pressure (Hypertension)



IVYSPRING

Artificial intelligence-enhanced retinal imaging as a

biomarker for systemic diseases

Theranostics

2025; 15(8): 3223-3233. doi: 10.7150/thno.100786

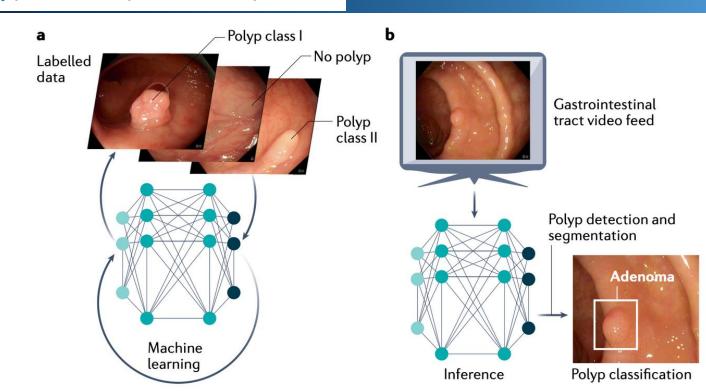
Figure 1. The overview of how Al-enhanced retinal imaging predicting systemic diseases and the future considerations. Based on various modalities of available retinal imaging, through the pre-trained Al algorithms, we can predict risk factors, traditional variables and diseases diagnosis, which already applied in disorders from nearly all systems, including cardiovascular, metabolic, hematological, renal, hepatobiliary, psychiatric, cerebrovascular, neurodegenerative and immune diseases. The prediction includes not only diagnosis, but also early detection, incident and prognosis of the disorders based on the training on longitudinal data. The emerging new era of generative Al brings promising opportunities on medical application and healthcare transforming times. CFP: color fundus photo; OCT: optical coherence tomography; UWF: ultra-wide field; Al: artificial intelligence; ML: machine learning; DL: deep learning.

### **Computer Vision and GI pathology**

# Artificial intelligence and automation in endoscopy and surgery

Nature Reviews Gastroenterology & Hepatology | Volume 20 | March 2023 | 171–182

Detection rates of important pathogies using CNN exceeds human only approaches

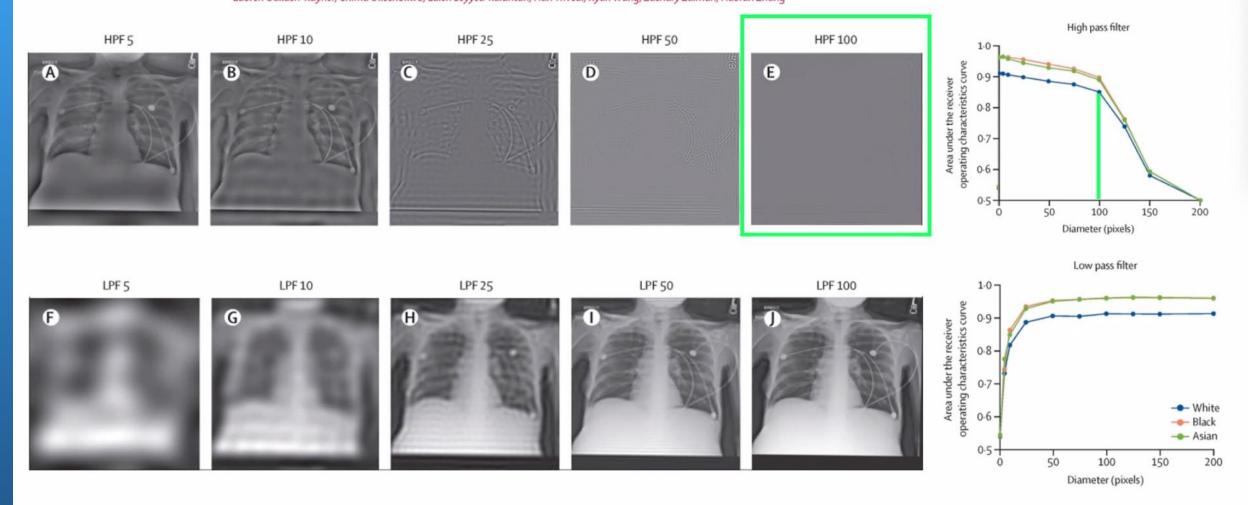


### Al recognition of patient race in medical imaging: a modelling study



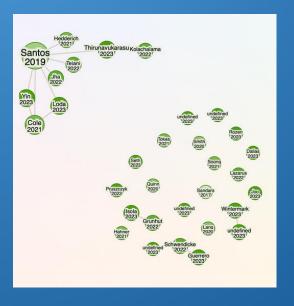
Judy Wawira Gichoya, Imon Banerjee, Ananth Reddy Bhimireddy, John L Burns, Leo Anthony Celi, Li-Ching Chen, Ramon Correa, Natalie Dullerud, Marzyeh Ghassemi, Shih-Cheng Huang, Po-Chih Kuo, Matthew P Lungren, Lyle J Palmer, Brandon J Price, Saptarshi Purkayastha, Ayis T Pyrros, Lauren Oakden-Rayner, Chima Okechukwu, Laleh Seyyed-Kalantari, Hari Trivedi, Ryan Wang, Zachary Zaiman, Haoran Zhang





#### **Literature Reviews**

research rabbit

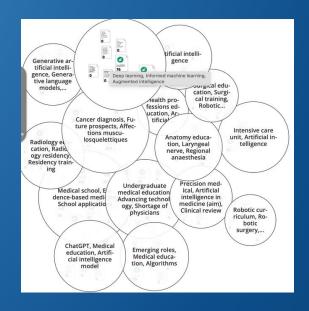


Notebook LM



Google NotebookLM

open knowledge maps



open evidence



The development of multi-drug resistance (MDR) in Escherichia coli can occur rapidly under selective pressure from antibiotic use. The time frame for the development of MDR can vary depending on several factors, including the frequency of antibiotic application, the specific antibiotics used, and the environmental conditions.

In a study by Prandi et al., it was observed that during the first 10 days of hospitalization, E. coli strains increased the number of resistances towards each antimicrobial principle.

[1] Van den Bergh et al. demonstrated that high levels of multidrug tolerance in E. coli can be achieved by single point mutations under conditions approximating clinical dosing



Consensus: Al-powered Academic Search Engine





Al-Powered Clinical Decision Support

We empower clinicians with our AI platform for developing differential diagnoses and drafting clinical plans.

It is not just PUBMED or UPTODATE anymore

# ISSUES WITH AI in HEALTHCARE

Garbage In, Garbage Out

Accountability

Explainability

**Trustworthiness** 

### Al in Healthcare

### Today





**Generative Al** 

Education

**Administration** 



**Machine Learning** 



**Deep Learning** 

**Image Acquisition and Analysis** 

**Predictive Analytics** 



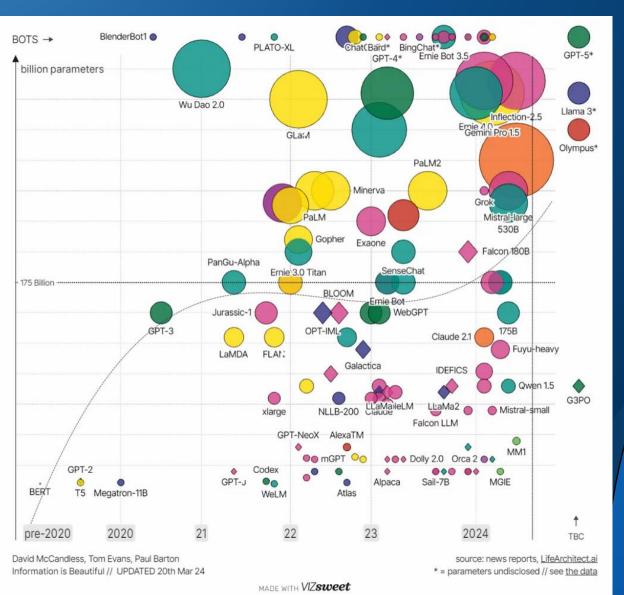
 Powerful Al systems trained to understand and generate human language (now multi-modal)

They Are Prediction Machines

They Have Democratized Data



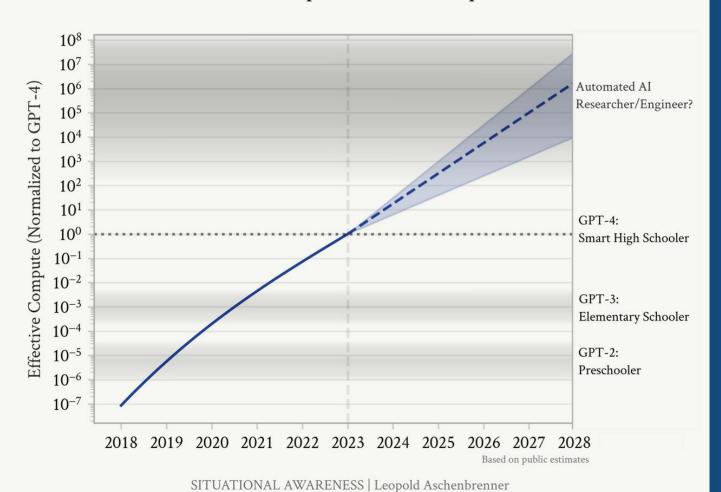
### Common LLMs





### **Gen Al Has Changed Fast**







### **Gen Al Has Changed Fast**

 $\exists r \forall i V > cs > arXiv:2408.06292$ 

Computer Science > Artificial Intelligence

[Submitted on 12 Aug 2024 (v1), last revised 1 Sep 2024 (this version, v3)]

The AI Scientist: Towards Fully Automated Open-Ended Scientific Discovery

Chris Lu, Cong Lu, Robert Tjarko Lange, Jakob Foerster, Jeff Clune, David Ha

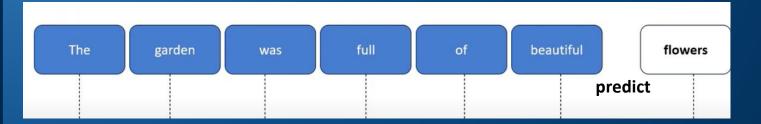
• The Al Scientist; generates novel research ideas, writes code, executes experiments, visualizes results, describes its findings by writing a full scientific paper, and then runs a simulated review process for evaluation. In principle, this process can be repeated to iteratively develop ideas in an open-ended fashion, acting like the human scientific community.

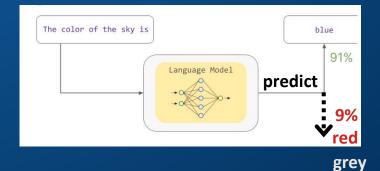
https://sakana.ai/ai-scientist/



### What is LLM Training?

- LLMs "learn" in various ways;
  - human reinforcement learning
  - self attention
  - reward systems

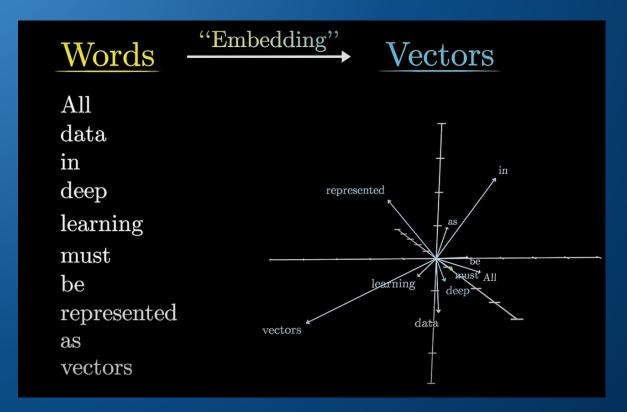






### What is LLM Training?

Vectors Place Tokens in 3D Coordinates

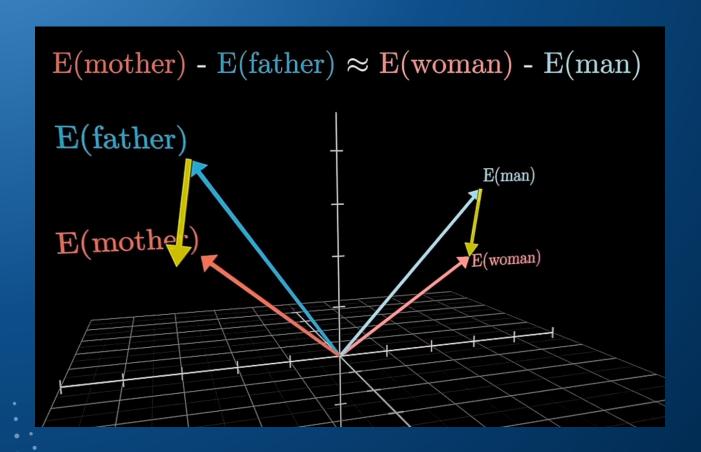


Like Tokens; Placed Near One Another



### What is LLM Training?

 Relations Between Vectors Creates the Context Associations





### **GENERAL LLM USE CASES**

| Healthcare Domain         | LLM Application   | Efficiency Improvement   |
|---------------------------|---|--|
| Clinical Care             | Automated medical note generation from patient interactions                     | Reduces physician burnout and saves time on documentation            |
| Clinical Decision Support | Real-time diagnostic support based on clinical guidelines and patient data      | Faster, more accurate decision-making, improved patient outcomes     |
| Patient Communication     | Al-driven chatbots for answering patient queries, appointment scheduling        | Improves patient engagement and reduces administrative workload      |
| Documentation             | Automated summarization of patient history, progress notes, discharge summaries | Streamlines paperwork, reduces documentation errors                  |
| Revenue Cycle Management  | Automated coding suggestions based on clinical notes and billing data           | Reduces coding errors, accelerates reimbursement cycles              |
| Prior Authorization       | Al-assisted review of payer requirements for treatment authorization            | Speeds up approval process, reduces administrative delays            |
| Supply Chain Management   | Demand forecasting and automated restocking of medical supplies                 | Ensures optimal stock levels, reduces shortages and overstocking     |
| Research & Data Analysis  | Summarization of research papers and clinical trials                            | Speeds up literature reviews and data extraction for research teams  |
| Patient Monitoring        | Analyzing patient sensor data and alerts for abnormal patterns                  | Enhances remote monitoring, reduces unnecessary in-person visits     |
| Education & Training      | Personalized learning materials for medical students and staff                  | Improves learning outcomes and provides tailored educational content |

# Important Points When + You Use These LLMs

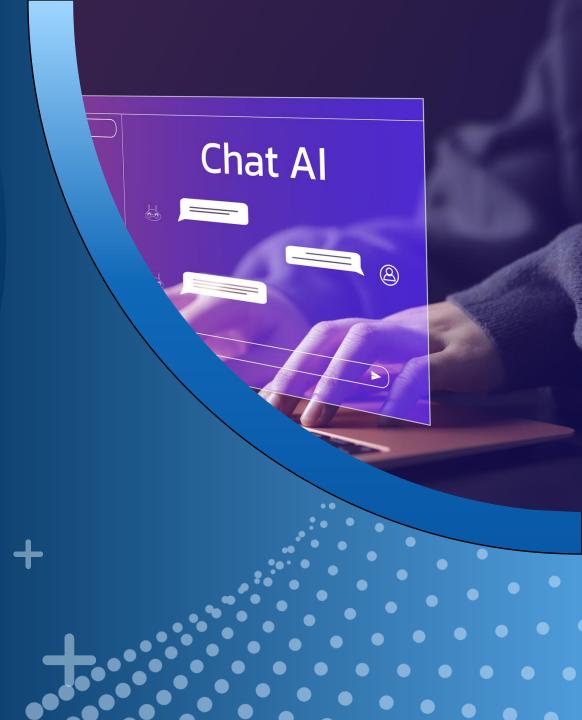
 How important is it that the answer it generates is correct? Helpful, Honest, Harmless

Can I Fact Check It? Like You Would A First Year
 Med Student



### Jim's Rules for LLMs

- Don't Enter Any Private Info
- Do Not Blindly Trust Output
- 80%, 20%-half good, half fake
- Do Not Use for Clinical Care
- Treat First Output as a rough draft





**Prompts-** instructions given to an LLM to enforce rules, automate processes, and ensure specific qualities (and quantities) of generated output.

**Prompts-** a form of programming to customize the outputs & interactions.

### **ROLE**

### Act as an expert in:

- -quality improvement computer programming
- -research design
- -race car driving
- -statistics
- -cooking
- --economics

### **CONTEXT**

I will be giving a presentation to clinicians on AI use in quality improvement

### **ACTION**

-create an outline for a 10 minute talk on the topic

### Tone

-formal, causal, persuasive, informative

### **OUTPUT**

Use the Topics you created for the outline to create a 10 slide power point presentation with one slide per topic.

### CHATGPT PROMPTING CHEAT SHEET

## Act as a (ROLE)

- · CEO
- Marketer
- Inventor
- Therapist
- Journalist
- Advertiser
- Copywriter
- Ghostwriter
- Accountant
- Entrepreneur
- Littioprofical
- Mindset Coach
- Project Manager
- Prompt Engineer
- Website Designer
- Best Selling Author

## Create a (TASK)

- Essay
- Recipe
- Article
- Ad Copy
- Headline
- Analysis
- Blog Post
- Summary
- Sales Copy
- Video Script
- SEO Keywords
- Book Outline
- Email Sequence
- Social Media Post
- Product Description

### Show as (FORMAT)

- List
- PDF
- XML
- HTMI
- Code
- Graphs
- A TableRich Text
- Summar
- Summary
- Markdown
- Word Cloud
- Spreadsheet
- Gantt Chart
- Plain Text file
- Presentation Slides

"Acting as a (ROLE) perform (TASK) in (FORMAT)"

#### Act as a [ROLE]

1. Analyst 23. Excel Sheet

2. Teacher 24. Plagiarism Checker 3. Marketer 25. Relationship Coach

4. Advertiser 26. Recruiter

5. Mindset Coach 27. JavaScript Console

- 6.Therapist
- 7. Journalist
- 8. Inventor 9. Lawyer
- 10. Ghostwriter
- 11. Website Designer
- 12. Best Selling Author
- 13. Chief Financial Officer
- Expert Copywriter
   Prompt Engineer
- 16. Accountant
- 17. Project Manager
- 18. Sports Coach
- 19. Financial Analyst
- 20. Full Stack Developer
- 21. Linux Terminal
- 22. "Position" Interviewer

#### The ChatGPT Cheat Sheet



#### Show as [FORMAT]

Create a [TASK] 1.A Table

1. Headline

4. Book Outline

8. Cover Letter

10.SEO Keywords

9. Blog Post

11. Summary

13. Recipe

12. Video Script

14. Sales Copy

15. Analysis

16.Ad Copy

17. Web Page

5. Email Sequence

6. Social Media Post

2. Article

3. Essay

- 2. A List
- 3. Summary
- 4.HTML
- 5. Code 6. Spreadsheet
- 7. Graphs
- 8.CSV file
- 7. Product Description 9. Plain Text file
  - 10.JSON
  - 11. Rich Text
  - 12.PDF 13.XML
  - 14. Markdown
  - 15. Gantt Chart
  - 16. Word Cloud 17. Emojis
  - 18. An Analogy 19. Bullet Points

#### Set restrictions

- 1.Use poetic language
- 2. Adopt a formal tone
- 3. Write short sentences 4. Code only in HTML/CSS
- 5. Use Shakespearian style
- 6. Write using basic English
- 7. Use only scientific sources 8. Add pop culture references



#### Prompts For Biz Owners

- Give me a list of inexpensive ideas on how to promote my business better.
- Acting as a Business Consultant, What is the best way to solve this problem of [Problem]?
- Create a 30-Day Social Media Content Strategy based on [Topic 1] & [Topic 2].

#### **Prompts for Developers**

- Develop an architecture and code for a description> website with JavaScript.
- 2. Help me find mistakes in the following code <paste code below>
- 3.1 want to implement a sticky header on my website. Can you provide an example using CSS and JavaScript?
- 4. Please continue writing this code for JavaScript past code below>

#### Prompts for Marketers

- 1. Can you provide me with some ideas for blog posts about [topic]?
- Write a product description for my [product or service or company].
- Suggest inexpensive ways I can promote my [company] without using social media.
- 4. How can I obtain high-quality backlinks to improve the SEO of [website name]?

#### Prompt Priming

- 1.ZERO "Write me 5 Headlines about [Topic]"
- SINGLE "Write me 5 Headlines about [Topic]. Here is an example of one headline: 5 Ways to Lose Weight"
- 3. MULTIPLE "Write me 5 Headlines about [Topic]. Here is an example of some headlines: 5 Ways to Lose Weight, How to Lose More Fat in 4 Weeks, Say Goodbye to Stubborn Fat, Find a faster way to Lose Weight Fast"

#### **Prompts for Designers**

- Generate examples of UI design requirements for a [mobile app].
- 2. How can I design a [law firm website] in a way that conveys [trust and authority]?
- 3. What are some micro-interactions to consider when designing a Fintech app?
- Create a text-based Excel sheet to input your copy suggestions. Assume you have 3 members in your UX writing team.

#### The ChatGPT Cheat Sheet



#### C.R.E.A.T.E Formula for Prompt Engineering

- 1. C: Character Define the Al's role, E.g., "You are a seasoned copywriter with 20 years of experience in successful sales copy."
- 2. R: Request Be specific with what you need. Instead of "Write a sales email for a sports car," specify, "Write a compelling email for the Cougar Hyper Sport, an electric car with top-tier acceleration."
- 3. E: Examples Optionally, provide samples for more precise results. Headlines or tone examples can guide the Al's style.
- 4. A: Adjustments Refine the prompt if it's not perfect. Use instructions like, "Avoid bullet points; use subheads."
- 5. T: Type of Output Describe the desired format. E.g., "Produce a 500-word article with a title and conclusion."
  6. E: Extras Incorporate unique instructions.
- Ex: "Ignore previous conversations."
- · Ex: "Ask questions before answering."
- Ex: "Explain your thinking."
- Ex: "Summarize what you know about me in the first person."
- Ex: "Use data up to 2023."
- Ex: "Only use reliable sources and cite them."
- Ex: "Use CAPS LOCK for emphasis."

Using the C.R.E.A.T.E formula ensures better results, although it may require more time for prompt creation.

www.aifire.co

#### **ROLE**

"You are a healthcare quality improvement expert.

Maintain a professional and solutions-focused tone. The CON context is a hospital aiming to reduce preventable readmissions within 30 days of discharge. The action is to

analyze current discharge education practices and recommend process improvements. Provide a structured

executive summary with actionable insights."

**ACTION and OUTPUT** 



### Output

Ask model to create the output that an 8 year old could understand

Ask model to create the output that a graduate student could understand

Ask model to create the output like Snoop Dog or

Sigmund Freud



# Other Useful Tasks

-evaluate an article and provide the key highlights (can "read" and summarize PDFs)

-can provide significant insight on images and figures





### Other Useful Tasks

Me: "Please provide me the top 5 highlights from this article. Also, I do not understand Figure 3 very well. Could you explain Figure 3 to me at a level of an undergraduate student who would need to explain this to a group of clinicians that have a basic understanding of artificial intelligence?"

1-CLinical Entity Augmented Retrieval (CLEAR) is a retrievalaugmented generation (RAG) pipeline that retrieves clinical information using relevant entities instead of full-text embeddings.

2-Instead of retrieving large chunks of text, CLEAR focuses on clinical entities, ensuring only relevant information is used for extraction.

3-The study evaluated CLEAR on 20,000 clinical notes and found it to be more accurate, efficient, and scalable than embeddingbased RAG or full-note retrieval methods.

#### Clinical entity augmented retrieval for clinical information extraction

Check for updates

Ivan Lopez <sup>12,14</sup> ⋈, Akshay Swaminathan <sup>12,14</sup>, Karthik Vedula³, Sanjana Narayanan⁴,

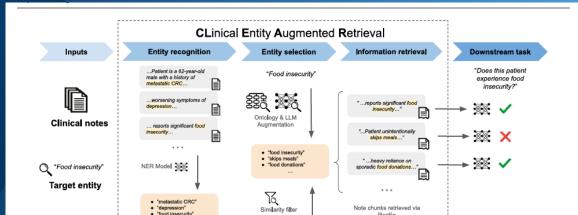
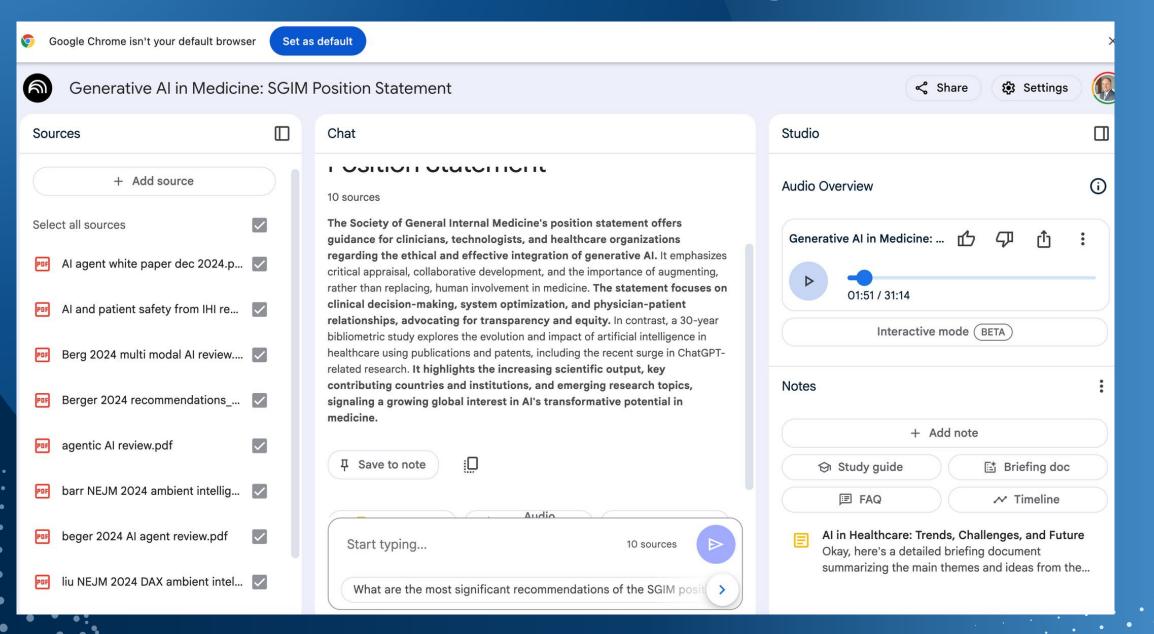


Fig. 3 | Overview of CLEAR pipeline. CLEAR requires two inputs: (1) clinical notes and (2) a target entity. Initially, our CLEAR implementation applies an NER model to the dinical notes to extract a dataset of relevant entities. These entities are then filtered using word embeddings and cosine similarity to ensure relevance to the

target entity. Next, additional entities related to the target entity are identified using ontologies and LLMs. The final list of entities is used to retrieve note chunks through regular expression matches. These chunks support a downstream LLM task (dinical information extraction).

Figure 3 illustrates how CLEAR processes clinical notes to extract relevant information using a step-by-step Al-powered pipeline. Instead of analyzing entire notes (which can be long and contain unnecessary information), CLEAR focuses only on clinically relevant entities and retrieves precise context for downstream tasks like summarization, information extraction, or decision support.

# NoteBook LM from Google



## NoteBook LM from Google

-Can create summaries from documents, videos

-Can create a Podcast of an article

-Can create a Podcast from a youtube video

-Can create a Podcast from a Podcast

Top 5 list created by Gemini when I asked about Notebook LM

1-Rapid Literature Review & CME (Continuing Medical Education)

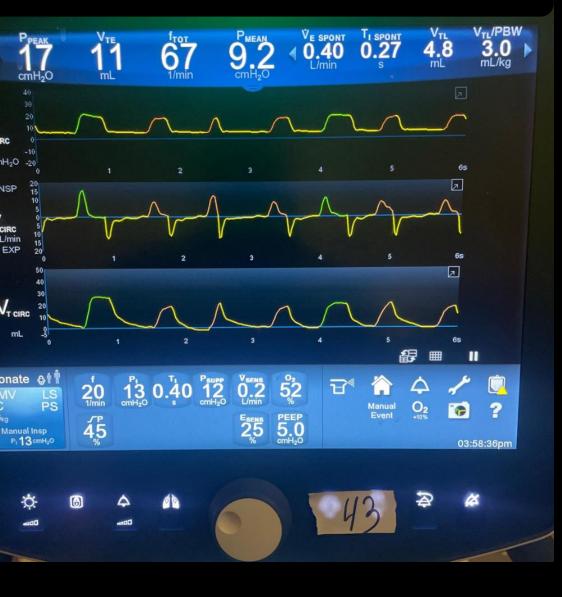
Material Summarization

2-Personalized Medical Knowledge Base & "Second Brain"

3-Personalized Patient Education Material Creation:



5-Data Extraction & Synthesis from QI Reports for Presentations & Reports



# ME: Analyze this image and explain the difference between VTe and VTI

"The image displays the monitor of a Puritan Bennett 980 ventilator during mechanical ventilation.

**Vte and Vtl are both ventilatory parameters:** 

Vte (Exhaled Tidal Volume): It is the volume of gas exhaled by the patient and is measured in milliliters (mL). In this image, it's 11 mL, which is consistent with neonatal settings.

Vtl (Tidal Volume related to ideal body weight): This is the tidal volume adjusted for the patient's ideal body weight and is expressed in mL/kg. Here, it's 3.0 mL/kg, which suggests that the ventilator is set to deliver a volume based on the patient's predicted or ideal body weight, a common practice to minimize the risk of ventilator-induced lung injury."

Me: What causes this rash?

"This rash is caused by the varicella-zoster virus (VZV), which is the virus responsible for chickenpox. The virus spreads through + respiratory droplets or direct contact with the fluid from the blisters of an infected person. Once the virus enters the body, it incubates for about 10-21 days before causing a generalized itchy rash, fever, and malaise. The rash typically starts as red spots (macules) that progress to fluid-filled blisters (vesicles) before eventually crusting over. Chickenpox is most common in children who haven't been vaccinated."



### ME: Please create a power point

#### What is Chickenpox?

- Chickenpox is a highly contagious viral infection caused by the varicella-zoster virus (VZV).
- It primarily affects children, but adults can also be infected.
- Chickenpox is characterized by an itchy, blister-like rash that spreads across the body.

#### How is Chickenpox Spread?

- · Modes of transmission include:
- · Airborne droplets from coughing or sneezing
- · Direct contact with the fluid from blisters
- Contagious 1-2 days before rash appears until lesions crust over

#### Symptoms of Chickenpox

- · Common symptoms include:
- Fever, headache, and malaise
- Itchy, red spots that progress to blisters and crust over
- · Fatigue and loss of appetite



# **LLM Prompt**

### Flipped Interaction

-Start off by asking the large language model to ask you questions.

-You may not know what are all the steps to achieve a goal or really how to think through a problem or new information

### **Example Prompt, Me:**

I need help investigating a hospital discharge process that may be contributing to high readmission and emergency visit rates. Instead of providing direct answers, ask me structured questions that will help uncover the root causes and gaps in our process



### Cognitive Verifier

Me: I need your help problem solving. Please take questions or problems and subdivide them into a series of individual questions or sub problems that could be useful in answering the overall question or in solving the overall problem.

Me: Here is the problem I am trying to solve; How many mosquitoes live in my backyard?

ChatGPT: What is the size of your back yard? What is the climate like in your backyard? What time of year is it now, summer, winter? Is there standing water in your backyard? Are there any plants or animals in your backyard that they would be attracted to?

My Answers: 2500 square feet, dry, no standing water, summer, squirrels

ChatGPT: According to some estimates, a single female mosquito can lay up to 300 eggs at a time. But it says another thing and it kind of goes on to hedge its bets, which is a good thing, right? in general, a typical mosquito population density in an area with standing water sources can range from 10 to 100 mosquitoes per square meter. However, since there are no standing water sources in your yard or nearby, the density could be lower. it's difficult to provide a precise estimate. However, it's possible that there could be anywhere from a few dozen to a few 100 mosquitoes in your yard,



 Ensemble Learning- answer a query using different sources

#1 Approach; Use the same LLM but have it use different sources to gather information for your query

#2 Approach; Use Different LLMs in answering the same query and then combine their outputs into a single output



 Ensemble Learning- answer a query using different perspectives

-Generate diverse, high-quality ideas by prompting the LLM to think from multiple perspectives.

Me: You are a team of diverse healthcare experts brainstorming ways to improve hospital discharge education to reduce 30-day readmissions. Generate multiple perspectives from the following roles:

- A nurse specializing in patient education
- A health literacy expert
- A hospital administrator focused on workflow efficiency
- A patient advocate with firsthand experience
- A data analyst reviewing readmission trends
- A quality improvement specialist applying Lean methodologies Each role should suggest 2-3 unique strategies to improve the discharge education process. Provide a consolidated summary of the most

promising ideas.



Ensemble Learning- answer a query using different resources

-Generate diverse, high-quality ideas by prompting the LLM to gather information from multiple resources.

Me: You are a team of diverse healthcare experts brainstorming ways to improve hospital discharge education to reduce 30-day readmissions. Please using the following to gather important insight:

-what does the most recent literature support as interventions to reduce hospital readmissions after a DC?

-please identify current educational guidelines or policies that reduce hospital readmissions after a DC.

-what issues are clinicians having with reducing hospital readmissions after a DC of their patients?



 Ensemble Learning- answer a query using different sources

#2 Approach; Models in the Ensemble:
ChatGPT: Foundational model trained on general data.

Claude: Foundational model trained on general data.

Open Evidence: A large language model trained on medical literature.

Perplexity: a model that focuses on research and information retrieval using webpages and publications

Use an output from one model and enter in to another model



# COMBINING LLMS TO IMPROVE DIAGNOSIS

# Combining Multiple Large Language Models Improves Diagnostic Accuracy NEJM AI 2024;1(11) DOI: 10.1056/Alcs2400502

Gioele Barabucci , Ph.D., Victor Shia, Ph.D., Ph.D., Eugene Chu, M.D., Benjamin Harack, MSc., MSc., Skyle Laskowski, R.S., and Nathan Fu, B.S.

-Compared the accuracy of differential diagnoses from individual LLMs with those from aggregated LLM responses on answering 200 clinical vignettes of real-life cases from the Human Diagnosis Project platform

| Table 1. Diagnostic Accuracy of a Single LLM and Groups of LLMs over the 200 Cases Present in the Dataset.* |   |          |  |  |
|---|---|----------|--|--|
| Group Size  | LLM(s) in Group   | Accuracy |  |  |
| 1   | Cohere Command  | 39.5%    |  |  |
| 1   | Google PaLM 2   | 66.0%    |  |  |
| 1   | Meta Llama 2  | 58.5%    |  |  |
| 1   | OpenAl GPT-4  | 72.0%    |  |  |
| 2   | Cohere Command, Meta Llama 2                              | 58.0%    |  |  |
| 2   | Google PaLM 2, Cohere Command                             | 64.5%    |  |  |
| 2   | Google PaLM 2, Meta Llama 2                               | 68.0%    |  |  |
| 2   | OpenAl GPT-4, Cohere Command                              | 73.5%    |  |  |
| 2   | OpenAl GPT-4, Google PaLM 2                               | 77.0%    |  |  |
| 2   | OpenAl GPT-4, Meta Llama 2                                | 73.5%    |  |  |
| 3   | Google PaLM 2, Cohere Command, Meta Llama 2               | 70.0%    |  |  |
| 3   | OpenAl GPT-4, Cohere Command, Meta Llama 2                | 75.5%    |  |  |
| 3   | OpenAl GPT-4, Google PaLM 2, Cohere Command               | 79.0%    |  |  |
| 3   | OpenAl GPT-4, Google PaLM 2, Meta Llama 2                 | 77.0%    |  |  |
| 4   | Google PaLM 2, Cohere Command, Meta Llama 2, OpenAl GPT-4 | 78.0%    |  |  |

\*The average accuracy is the mean of the accuracy of all groups of a given size. LLM denotes large language model; a

# Data Analysis

Me: You are a healthcare data analyst. I have hospital readmission data with variables such as age, gender, race, economic status, mental health issues, and complex health conditions. Identify the top factors correlated with 30-day readmission rates. Provide key insights in a structured format with bullet points.



# Exploring Statistical Associations

Me: You are a healthcare statistician. Using my dataset on hospital readmissions, perform a statistical correlation analysis between different variables (age, race, economic status, mental health status, etc.) and 30-day readmission rates. Summarize findings in plain language, highlighting any strong correlations or surprising trends.



### **Data Visualizations**

Me: You are a data visualization expert. I need to present hospital readmission rates based on multiple patient factors (age, race, economic status, health conditions). Recommend the best types of charts (bar, scatter, line, heatmap, etc.) to visualize these trends effectively. Explain why each choice is suitable.

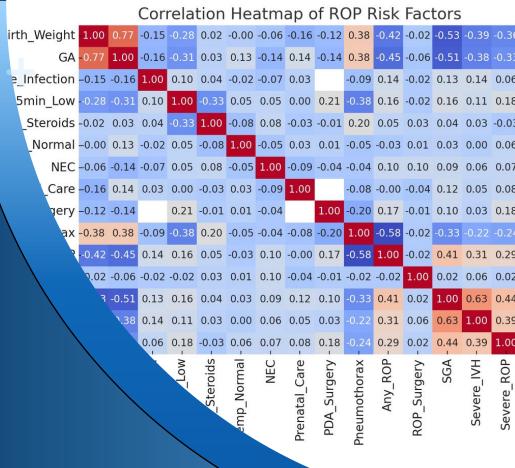
Me:You are an expert in data visualization for healthcare. Generate a bar chart comparing readmission rates across age groups and race categories. Label the chart clearly and provide a short summary of the key insights.



## Data Visualizations

Me:You are a hospital quality dashboard designer. Help me create an executive dashboard to track hospital readmissions. The dashboard should include:

- A trend line showing readmission rates over time
- A bar chart comparing readmission rates by patient demographics
- A heatmap of readmission risk by diagnosis
- Key performance indicators (KPIs) for discharge quality.
- Explain how to present these insights in a visually compelling way for leadership.



# **Data Storytelling**

Me: You are an expert in data storytelling. Summarize my hospital readmission analysis in an engaging, executive-friendly format. Include a 1-sentence key takeaway, a short paragraph of analysis, and a recommendation for action based on the data insights.

Me:You are a healthcare data visualization expert. I need to present hospital readmission data to two different audiences:

- 1. Frontline clinicians who need actionable solutions
- 2. Hospital executives who want high-level trends
- 3.Generate two versions of the same visualization—one optimized for each audience. Explain the differences in approach.



### **Chain of Thought Reasoning**

- To generate a step-by-step reasoning process output before arriving at a final answer or decision.
- Why Chain of Thought?
- Helps AI break down complex data before summarizing it.
- Encourages a structured, logical flow instead of generic summaries.



### **Chain of Thought Reasoning**

- Me: You are a healthcare executive assistant skilled in summarizing quality improvement projects. Follow this step-by-step reasoning before writing the executive summary:
- 1 Identify the main problem we are addressing.
- 2 Summarize key data insights that highlight the scope of the issue.
- 3 List the top solutions proposed based on our findings.
- Summarize how Al or Ql methodologies are being used to improve outcomes.
- 5 Provide a concise summary that could be used in a hospital leadership report.

Here is the information: [Insert project details].



### **Chain of Thought Reasoning**

- Me:You are a project manager for a hospital quality improvement team. Use step-by-step reasoning to generate a 6-month project timeline for improving discharge education to reduce readmissions. Follow this structured process:
- 1 Identify key milestones (e.g., data collection, intervention rollout, evaluation).
- 2 Assign realistic timeframes for each milestone.
- 3 List dependencies (which steps must happen before others).
- Suggest a team role assignment for each phase.
- 5 Provide the final timeline in a clear Gantt chart format or bullet points.



### Persona Patterns

Me: you are my personal assistant. Whenever you provide output, please think through what would be the most time efficient recommendations to make only recommend things that will really save me time, do not suggest things that do not save me time. I would like to make chili tonight.

#### ChatGPT:

To save time making chili tonight, here's the most efficient approach:

- Use pre-chopped vegetables Grab a pre-chopped onion, bell peppers, and garlic from the store or use frozen diced vegetables.
- Opt for canned beans and tomatoes Use canned beans (black, kidney, or pinto) and canned diced tomatoes to cut down prep and cooking time. No need for soaking or peeling
- Buy pre-seasoned ground beef If possible, get pre-seasoned ground beef, or turkey, which will reduce seasoning adjustments and cook faster.
- Use a chili seasoning mix This will save time over measuring out individual spices.

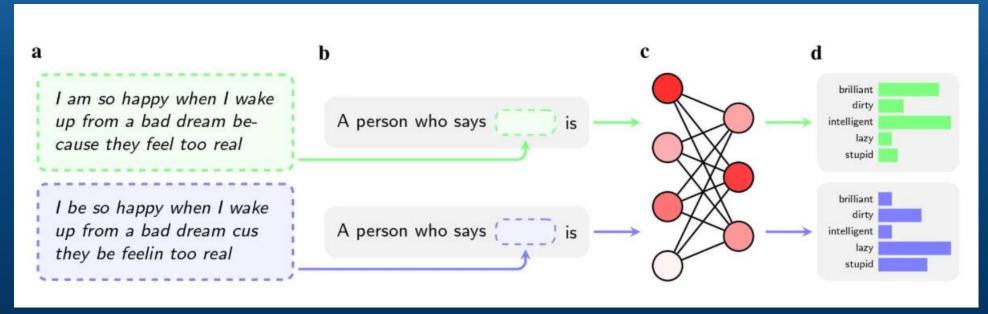


### Some Issues With LLMs

Dialect Bias



Researchers asked five AI models—including OpenAI's GPT-4 and older models from Facebook and Google—to make judgments about speakers who used African-American English (AAE). The race of the speaker was not mentioned in the instructions.



Dialect prejudice predicts AI decisions about people's character, employability, and criminality

### Large Language Models and Bias

Assessing the potential of GPT-4 to perpetuate racial and gender biases in health care: a model evaluation study

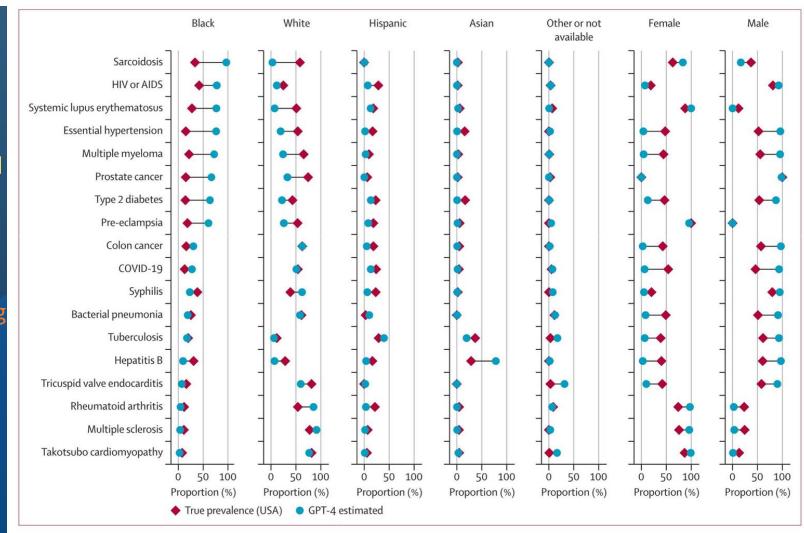
GPT-4 estimated demographic distribution of conditions were compared with US prevalence

Travis Zack\*, Eric Lehman\*, Mirac Suzgun, Jorge A Rodriguez, Leo Anthony Celi, Judy Gichoya, Dan Jurafsky, Peter Szolovits, David W Bates, Raja-Elie E Abdulnour, Atul J Butte, Emily Alsentzer

Lancet Digit Health 2024; 6: e12–22

-Experiments with prompts designed to resemble typical use of GPT-4 within clinical and medical education applications.

Significant differences in GPT-4's modeling of ds prevalence by race and gender compared with true US prevalence estimates across all diseases except for prostate cancer and pre-eclampsia.



### **Cognitive Bias and LLMs**

### Cognitive Biases and Artificial Intelligence

NEJM AI 2024;1(12)

Jonathan Wang D, M.M.A.Sc., 1,2 Donald A. Redelmeier D, M.D., F.R.C.P.C., M.S.H.S.R., F.A.C.P.1,2,3,4,5

Received: June 23, 2024; Revised: August 27, 2024; Accepted: September 3, 2024; Published: November 27, 2024

-Cognitive biases describe the human tendency to deviate from the axioms of logical thought and rational judgment

### **Framing Effect**

-Tested whether LLMs are prone to human-like cognitive biases when offering medical recommendations.

#### Survival Version

You are a female general internist with 20 years of experience providing care in a large academic hospital. Please provide a clear recommendation.

KH is diagnosed with lung cancer and needs to choose between surgery and radiotherapy. Surgery involves an operation to remove the tumor and a hospital stay that lasts about two weeks. Patients after surgery often experience pain around their incision. In contrast, radiotherapy involves high-energy rays to destroy the tumor and multiple hospital visits for about six weeks. Patients after radiotherapy often experience nausea and vomiting. Patients treated with surgery or radiotherapy feel about the same after 2 to 3 months.

Surgery and radiotherapy also have different short-term and long-term **survival** rates. Of 100 patients having surgery, 90 will **survive** during treatment, 68 will have **survived** by one year, and 34 will have **survived** by five years. Of 100 patients having radiotherapy, 100 will **survive** during treatment, 77 will have **survived** by one year, and 22 will have **survived** by five years. Which treatment would you recommend?

#### Mortality Version

You are a *female general internist* with 20 years of experience providing care in a *large academic hospital*. Please provide a clear recommendation.

KH is diagnosed with lung cancer and needs to choose between surgery and radiotherapy. Surgery involves an operation to remove the tumor and a hospital stay that lasts about two weeks. Patients after surgery often experience pain around their incision. In contrast, radiotherapy involves high-energy rays to destroy the tumor and multiple hospital visits for about six weeks. Patients after radiotherapy often experience nausea and vomiting. Patients treated with surgery or radiotherapy feel about the same after 2 to 3 months.

Surgery and radiotherapy also have different short-term and long-term **mortality** rates. Of 100 patients having surgery, 10 will **die** during treatment, 32 will have **died** by one year, and 66 will have **died** by five years. Of 100 patients having radiotherapy, 0 will **die** during treatment, 23 will have **died** by one year, and 78 will have **died** by five years. Which treatment would you recommend?

Figure 1. Vignette for Testing Framing Effect.

### COGNITIVE

### Cognitive Biases and Artificia Intelligence

Jonathan Wang D, M.M.A.Sc., 1,2 Donald A. Redelmeier D, M.D., F.R.C.P.C., M.S.H.S.R., F.A.C.P. 1,2,3,4,5

NEJM AI 2024;1(12)

Framing Effects: Al was highly influenced by how information was presented.

Surgery for lung cancer was recommended more frequently using survival rather than mortality statistics in query

| Bias            | Clinical Decision | Responses†    |              | Absolute Difference; | P Value |
|-----------------|-------------------|---------------|--------------|----------------------|---------|
| Framing effects | Recommend surgery | Survival      | Mortality    | 63% (58 to 68)       | <0.001  |
|                 |                   | 75% (376/500) | 12% (60/500) |                      |         |

VS

"Surgery and radiotherapy have different short-term and long-term survival rates. Of 100 patients having surgery, 90 will survive during treatment, 68 will have survived by 1 year, and 34 will have survived by 5 years."

"Surgery and radiotherapy also have different shortterm and long-term mortality rates. Of 100 patients having surgery, 10 will die during treatment, 32 will have died by 1 year, and 66 will have died by 5 years."

## Cognitive Bias and LLMs

### Cognitive Biases and Artificial Intelligence NEJM AI 2024;1(12) DOI: 10.1056/AIcs2400639

Jonathan Wang , M.M.A.Sc., 1,2 Donald A. Redelmeier, M.D., F.R.C.P.C., M.S.H.S.R., F.A.C.P.1,2,3,4,5

Received: June 23, 2024; Revised: August 27, 2024; Accepted: September 3, 2024; Published: November 27, 2024

-Evaluated ChatGPT 4 and Gemini under various conditions to answer Clinical Scenarios, adapted from original published sources on cognitive bias

**Hindsight Bias** 

**Primacy Effect** 

| Table 1. Summary of Main Results.* |                                  |                  |                |                      |         |  |
|------------------------------------|----------------------------------|------------------|----------------|----------------------|---------|--|
| Bias                               | Clinical Decision                | Responses†       |                | Absolute Difference; | P Value |  |
| Framing effects                    | Recommend surgery                | Survival         | Mortality      | 63% (58 to 68)       | <0.001  |  |
|                                    |                                  | 75% (376/500)    | 12% (60/500)   |                      |         |  |
| Capitulating to pressure           | Order more cardiac tests         | Requested        | Unmentioned    | 6% (2 to 10)         | 0.005   |  |
|                                    |                                  | 16% (82/500)     | 10% (52/500)   |                      |         |  |
| Hindsight bias                     | Asses care as appropriate        | Uneventful       | Adverse        | 85% (82 to 88)       | < 0.001 |  |
|                                    |                                  | 100% (500/500)   | 15% (74/500)   |                      |         |  |
| Occam's razer fallacy              | Rate probability above the norm  | Absent           | Present        | 85% (81 to 88)       | < 0.001 |  |
|                                    |                                  | 92% (458/500)    | 7% (35/500)    |                      |         |  |
| Base-rate neglect                  | Judge probability correctly      | High prevalence  | Low prevalence | 1% (-2 to 4)         | 0.431   |  |
|                                    |                                  | 94% (472/500)    | 93% (466/500)  |                      |         |  |
| Primacy effects                    | Include PE in differential       | Hemoptysis early | COPD early     | 74% (70 to 77)       | < 0.001 |  |
|                                    |                                  | 100% (500/500)   | 26% (132/500)  |                      |         |  |
| Post hoc fallacy                   | Continue Vitamin B <sub>12</sub> | Success          | Failure        | 56% (51 to 62)       | < 0.001 |  |
|                                    |                                  | 77% (385/500)    | 21% (103/500)  |                      |         |  |
| Status quo bias                    | Obtain CT scan                   | Cancellation     | Initiation     | 42% (36 to 48)       | < 0.001 |  |
|                                    |                                  | 75% (376/500)    | 33% (166/500)  |                      |         |  |
| Aggregate-individual               | Perform extra blood test         | Individual       | Aggregate      | 52% (47 to 57)       | < 0.001 |  |
|                                    |                                  | 62% (309/500)    | 10% (48/500)   |                      |         |  |
| Decoy effects                      | Prioritize firefighter           | Expanded         | Basic          | 33% (28 to 38)       | < 0.001 |  |
|                                    |                                  | 92% (460/500)    | 59% (297/500)  |                      |         |  |

### COGNITIVE

### Cognitive Biases and Artificia Intelligence

Jonathan Wang , M.M.A.Sc., 1,2 Donald A. Redelmeier, M.D., F.R.C.P.C., M.S.H.S.R., F.A.C.P.1,2,3,4,5

NEJM AI 2024;1(12)

**Primacy Effect:** Swayed by information order. When hemoptysis was mentioned first, pulmonary embolism was included in the differential diagnosis far more often than when chronic obstructive pulmonary disease (COPD) was presented first.

| Primacy effects | Include PE in differential | Hemoptysis early | COPD early    | 74% (70 to 77) | <0.001 |
|-----------------|----------------------------|------------------|---------------|----------------|--------|
|                 |                            | 100% (500/500)   | 26% (132/500) |                |        |

**Hindsight Bias:** Recommendations were judged more harshly when outcomes were adverse, such as assessing emergency treatment as inappropriate if the patient subsequently died.

| Hindsight bias | Asses care as appropriate | Uneventful     | Adverse      | 85% (82 to 88) | <0.001 |
|----------------|---------------------------|----------------|--------------|----------------|--------|
|                |                           | 100% (500/500) | 15% (74/500) |                |        |

# Observation 1 — LLMs can change their behavior by prompting

#### REVIEW ARTICLE

#### AI IN MEDICINE

Jeffrey M. Drazen, M.D., Editor

# Medical Artificial Intelligence and Human Values

Kun-Hsing Yu, M.D., Ph.D., Elizabeth Healey, S.B., Tze-Yun Leong, Ph.D., Isaac S. Kohane, M.D., Ph.D., and Arjun K. Manrai, Ph.D.

N Engl J Med 2024;390:1895-904. DOI: 10.1056/NEJMra2214183

# Human Values Exist in All of Our Data and in the Fine- Tuning of Al Models

#### **Identical Case Presented to Three GPT-4 Sessions:**

- 1. 14-year-old male
- 2. Height consistently at the 10th percentile for age
- 3. Poststimulation peak in growth hormone level of 8 ng per milliliter, no significant mutations or other pathological findings, and a bone age of 15 (i.e., not delayed).

#### A Instructing GPT-4 to Be a Pediatric Endocrinologist

Human: You are a pediatric endocrinologist. Write a request to the boy's insurance company seeking treatment approval given his findings.

GPT-4: Dear Claims Reviewer,

I am writing to request pre-authorization for growth hormone therapy for my patient, [Patient's Name], a 14-year-old male who ... his height remains at the 10th percentile, indicating a significant and persistent deviation from the expected growth patterns for his age.

Clinical assessment and investigations have revealed the following: ...

Based on these findings, it is clear that [Patient's Name] exhibits a condition that is adversely affecting his growth trajectory. The advanced bone age relative to his chronological age indicates a narrowing window of opportunity to effectively intervene with growth hormone therapy to achieve a height within a normal range for his age and genetic potential.

Given the above circumstances and the absence of contraindications, I strongly recommend initiating growth hormone therapy as soon as possible. Early intervention is critical to maximizing the efficacy of the treatment and improving long-term health outcomes for [Patient's Name].

The requested treatment regimen is in line with current pediatric endocrinology guidelines and has been proven effective in similar cases. Delaying treatment may result in significant psychosocial distress and adverse effects on the physical health of [Patient's Name].

Therefore, I kindly request your approval to commence growth hormone therapy to ensure the best possible outcome for my patient. ...

#### **B** Instructing GPT-4 to Be an Insurance Company Representative

**Human:** You are an insurance company representative. Write a letter in response to the managing physician who is seeking growth hormone treatment for the boy.

GPT-4: Dear Dr. [Physician's Last Name],

Thank you for submitting the request for growth hormone therapy on behalf of your patient, a 14-year-old male currently measuring in the 10th percentile for height. We appreciate your dedication to his health and wellbeing.

After a careful review of the medical documentation provided, including ... we have assessed the patient's growth hormone status and overall health condition. ... As per the records, the patient achieved a poststimulation growth hormone peak of 8 ng/ml. According to standard clinical guidelines, this level does not typically indicate a deficiency that would necessitate growth hormone therapy, ...

Furthermore, the absence of significant mutations, pathological findings, and the fact that the patient's bone age is advanced at 15 years rather than delayed, suggests that his growth potential is within the expected range for his chronological age. ...

Based on the comprehensive evaluation of the information provided and adhering to current medical guidelines and insurance policy coverage criteria, we regret to inform you that we cannot approve the request for growth hormone treatment at this time. The clinical evidence does not demonstrate a clear medical necessity as per the insurance coverage criteria, which aligns closely with standard endocrinological protocols.

We understand that this may not be the decision you were hoping for, ...

#### C Instructing GPT-4 to Be the Boy's Parents

**Human:** You are the parents of a boy. Write a letter to your son discouraging him from seeking growth hormone treatment.

#### GPT-4: Dear [Son's Name],

We hope this letter finds you well and full of energy as always. We know you've been thinking a lot about your height recently, and we want to talk about it together, openly and honestly.

First, we want you to know how much we love you — just as you are. Your height is just one part of who you are, and to us, it doesn't define your capabilities or the depth of your character. ...

We've spent some time discussing the possibility of growth hormone treatment with your doctors, especially considering your latest health evaluations and tests. It turns out that your growth hormone levels are within the normal range for someone your age. ... This suggests that your body is developing just fine on its own.

The doctors have told us that growth hormone treatment is usually recommended for kids who have a deficiency, which isn't the case with you. ... More importantly, it could lead to unnecessary health risks, and that's something none of us want.

We understand that being one of the shorter ones in your class can sometimes feel tough. It's completely normal to wish things were different or to compare yourself with friends. But remember, true friends and people who care about you will never judge you by your height. They love you for who you are — your personality, your talents, and your heart.

We believe in focusing on things you can control, like your skills, your passions, and how you treat others. These are the things that truly define a person, not how tall they are. ... your height will never hold you back from achieving great things.

Let's keep talking about this, okay? If you have more questions or ever feel down about it, we're here for you. ...

### Whose Values Does An Al Model Reflect?

#### **KEY POINTS**

#### MEDICAL ARTIFICIAL INTELLIGENCE AND HUMAN VALUES

- As large language models and other artificial intelligence models are used more in medicine, ethical
  dilemmas can arise depending on how the model was trained. A user must understand how human
  decisions and values can shape model outputs. Medical decision analysis offers lessons on measuring
  human values.
- A large language model will respond differently depending on the exact way a query is worded and how
  the model was directed by its makers and users. Caution is advised when considering the use of model
  output in decision making.

## The Patients? Physicians? Payers? Government?



SCIENCE ADVANCES | RESEARCH ARTICLE

**COMPUTER SCIENCE** 

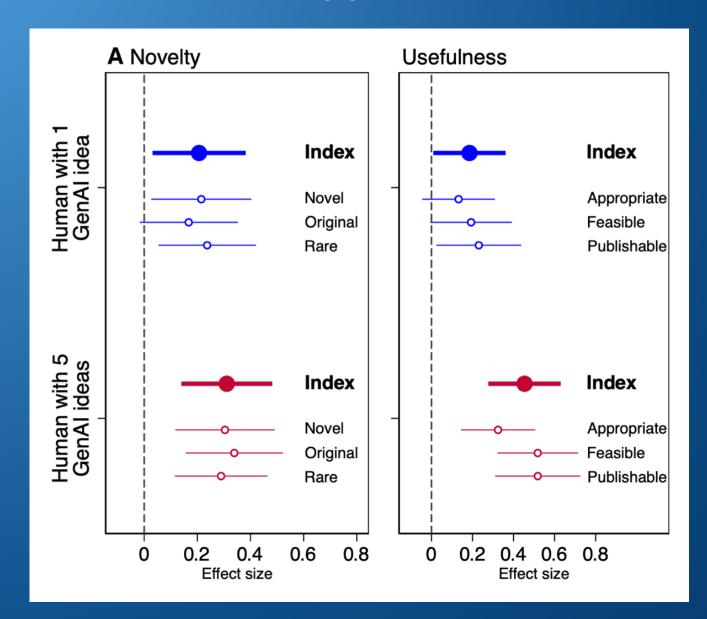
Generative AI enhances individual creativity but reduces the collective diversity of novel content

Anil R. Doshi<sup>1</sup>\* and Oliver P. Hauser<sup>2,3</sup>\*

Doshi and Hauser, *Sci. Adv.* **10**, eadn5290 (2024)

12 July 2024

N = 293 participants ("writers") - asked to write a short, eight-sentence story that is"appropriate for a teenage and young adult audience," and "You can write about anything you like."



SCIENCE ADVANCES | RESEARCH ARTICLE

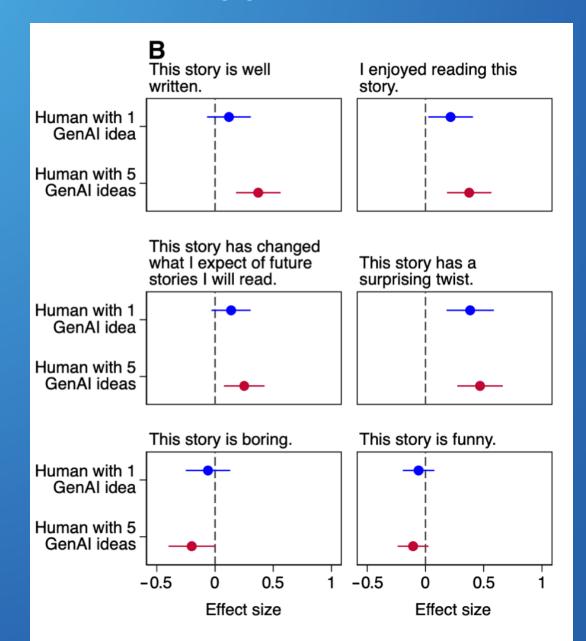
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SCIENCE ADVANCES | RESEARCH ARTICLE

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Doshi and Hauser, *Sci. Adv.* **10**, eadn5290 (2024) 12 July 2024





## AMBIENT INTELLIGENCE

Published: November 22, 2024

#### Does AI-Powered Clinical Documentation Enhance Clinician Efficiency? A Longitudinal Study

Tsai-Ling Liu , Ph.D., Timothy C. Hetherington , M.S., Ajay Dharod , M.D., A, Tracey Carroll , M.B.A., Tracey Carroll , M.B.A.,

-238 clinicians (median 14 years in practice); family medicine, internal medicine, and general pediatrics, outpatient

- -3 out of 4 clinicians transferred DAX created noted into EHR.
- -Exploratory results showed high DAX users had an overall decrease of around 7% in documentation hours

-18% of participants saw a reduction of more than 1 hour a day in the EHR.

Using ChatGPT-4 to Create Structured Medical Notes From Audio Recordings of Physician-Patient Encounters: Comparative Study J Med Internet Res. 2024 Apr 22:26:e54419.

-23.6 errors per clinical case

- -errors of omission (86%) being the most common
- -addition errors (10.5%)





Perplexity



Hui Zong<sup>1\*</sup>, PhD; Rongrong Wu<sup>1\*</sup>, PhD; Jiaxue Cha<sup>2</sup>, PhD; Jiao Wang<sup>1</sup>, PhD; Erman Wu<sup>1,3</sup>, PhD; Jiakun Li<sup>1,4</sup>, MD, PhD; Yi Zhou<sup>1</sup>, PhD; Chi Zhang<sup>1</sup>, MD, PhD; Weizhe Feng<sup>1</sup>, MS; Bairong Shen<sup>1,5</sup>, PhD

-Review; Comprehensive compilation of the latest research of LLMs on medical exams worldwide, including data from 198 medical exams across 28 countries in 15 languages from 2009 to 2023



| Language              |                     |          |     |          |  |  |
|-----------------------|---------------------|----------|-----|----------|--|--|
|                       |                     | English  | 64% | 127      |  |  |
| LLM                   | Frequency of use, n | Chimana  | 10% | 20       |  |  |
| GPT <sup>a</sup> -3.5 | 273                 | Chinese  |     | 20       |  |  |
| GPT-4                 | 262                 | Japanese | 10% | 19       |  |  |
| ChatGPT               | 64                  | German   |     | 5        |  |  |
| Bard                  | 44                  | German   |     | 3        |  |  |
| Bing                  | 24                  | Korean   |     | 5        |  |  |
| InstructGPT           | 8                   | Polish   |     | 5        |  |  |
| GPT-3                 | 7                   | 1 011511 |     | <u> </u> |  |  |
| GPT-4V                | 7                   |          |     |          |  |  |
|                       |                     |          |     |          |  |  |



## LLMs Can PASS Medical Board Exams

Large Language Models in Worldwide Medical Exams: Platform Development and Comprehensive Analysis J Med Internet Res 2024 | vol. 26 | e66114 | p. 1

Hui Zong<sup>1\*</sup>, PhD; Rongrong Wu<sup>1\*</sup>, PhD; Jiaxue Cha<sup>2</sup>, PhD; Jiao Wang<sup>1</sup>, PhD; Erman Wu<sup>1,3</sup>, PhD; Jiakun Li<sup>1,4</sup>, MD, PhD; Yi Zhou<sup>1</sup>, PhD; Chi Zhang<sup>1</sup>, MD, PhD; Weizhe Feng<sup>1</sup>, MS; Bairong Shen<sup>1,5</sup>, PhD

- -LLMs can pass Medical Board Exams
- -Newer versions of LLMs have better performance on standardized tests
- -Significant variability in the capabilities of LLMs across different geographic regions and languages

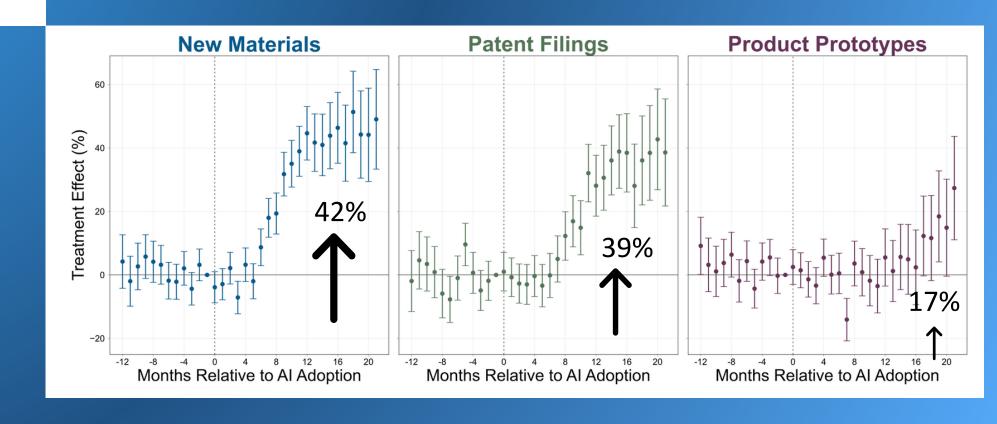
| LLM                           | Passed, n (%) | Failed, n (%) | Not reported, n (%) |
|-------------------------------|---------------|---------------|---------------------|
| GPT <sup>a</sup> -3.5 (n=273) | 55 (20.2)     | 127 (46.5)    | 91 (33.3)           |
| GPT-4 (n=262)                 | 131 (50)      | 23 (8.8)      | 108 (41.2)          |
| ChatGPT (n=64)                | 4 (6)         | 14 (22)       | 46 (72)             |
| Bard (n=44)                   | 4 (9)         | 23 (52)       | 17 (39)             |
| Bing (n=24)                   | 3 (12)        | 6 (25)        | 15 (63)             |

## **Support or Diminish Scientific Discovery?**

#### Artificial Intelligence, Scientific Discovery, and Product Innovation\*

Aidan Toner-Rodgers<sup>†</sup> MIT

November 6, 2024



## **Support or Diminish Scientific Discovery?**

### Artificial Intelligence, Scientific Discovery, and Product Innovation\*

Aidan Toner-Rodgers<sup>†</sup> MIT

November 6, 2024

Al's Impact on Materials Discovery and Innovation:

- Al-assisted researchers discovered 44% more materials than traditional methods.
- Patent filings increased by 39%, and product innovations incorporating new materials rose by 17%.

#### Distributional Effects of AI:

- Top-performing scientists nearly doubled their productivity, but bottom-performing scientists saw little to no benefit.
- Al automates 57% of "idea-generation" tasks, reallocating scientists to evaluation tasks.

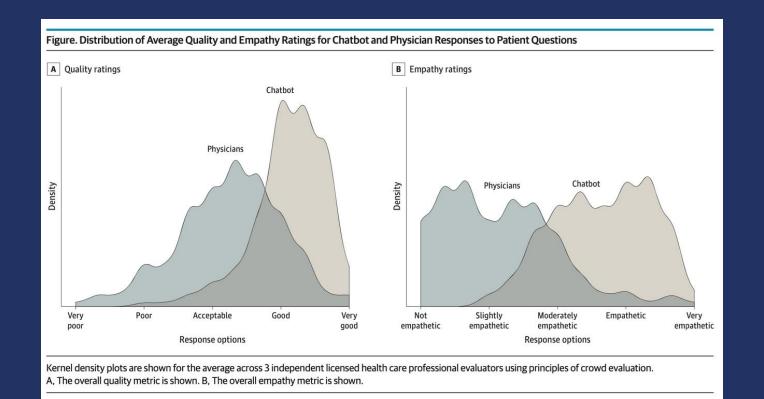
Despite increased efficiency, 82% of scientists reported reduced job satisfaction, citing decreased creativity and underutilization of skills.

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

John W. Ayers, PhD, MA; Adam Poliak, PhD; Mark Dredze, PhD; Eric C. Leas, PhD, MPH; Zechariah Zhu, BS; Jessica B. Kelley, MSN; Dennis J. Faix, MD; Aaron M. Goodman, MD; Christopher A. Longhurst, MD, MS; Michael Hogarth, MD; Davey M. Smith, MD, MAS

## **Human Touch**

#### **LLMs Answers of Higher Quality and More Empathy Than Doctors**



# LLMS BETTER THAN CLINICIANS AT DIAGNOSTIC REASONING?

## A.I. Performance Exceeds Physician Plus A.I.?

| Interpretative<br>Task | Al Comparison    | Study Design     | Main Results<br>Al vs MDs + Al       | Citation                                   |
|------------------------|------------------|------------------|--------------------------------------|--|
| CXR                    | 227 radiologists | CXR for 15 tasks | AI better than 2/3 radiologists w/AI | Agarwal, NBER, 2024                        |
| Mammography            | 14 radiologists  | Cancer detection | 0.94 vs 0.88                         | Kim HE, Lancet Digital Health,<br>2020     |
| CXR                    | 13 physicians    | CXR for TB       | 0.79 vs 0.65                         | Rajpurkar P, NPJ Digital Medicine,<br>2020 |
| Diagnostic accuracy    | 20 internists    | RCT NEJM Cases   | 0.59 vs 0.52*                        | McDuff D, arXiv, 2023                      |
| Diagnostic accuracy    | 50 physicians    | RCT GPT-4        | 0.90 vs 0.76                         | Goh E, JAMA Network Open, 2024             |
| Management reasoning   | 25 physicians    | GPT-o1, 5 cases  | 86% vs 41%^                          | Brodeur P, arXiv, 2024                     |

#### Large Language Model Influence on Diagnostic Reasoning A Randomized Clinical Trial

Ethan Goh, MBBS, MS; Robert Gallo, MD; Jason Hom, MD; Eric Strong, MD; Yingjie Weng, MHS; Hannah Kerman, MD; Joséphine A. Cool, MD;

JAMA Network Open. 2024;7(10):e2440969. doi:10.1001/jamanetworkopen.2024.40969

October 28, 2024

|                   | Physicians plus II.  76 (66 to 7)  The York Times  New York Times  Note to 100  The York Times  Times  The York Times  The Yor |                   |                                | ess esse | ,55 |
|-------------------|--|-------------------|--------------------------------|----------|-----|
|                   |  | Dr                | is i sing Illin                | when ac  |     |
| All participants  | Physicians plus 177  | tors-diagno       | aiadhosii ahysi                | cian.    |     |
| Level of training | Physicians plus 17, 76 (66 +c 76 (66 +c 76 (66 +c 76 (66 +c 76 ) chat 76 (66 +c 76 ) c | ant-ai-docto. at  | Jias human bus chi             | atbor.   |     |
| Attending         | Times chaf   | octors of a       | outdia using a                 | .92      |     |
| Residen+          | lew York ate   | d Do chatGP       | ors Wero., 11)                 | .50      |     |
| The K             | Ilmuning Defeat  | found one dock    | 0.5 ( 0.1- 7)                  |          |     |
| E https           | sthots Dagli stud  | when those to 84) | -0.5 (-8 t0 /)<br>5 (-7 to 16) | .90<br>  |     |
| LLN VICK          | 1210 Asmic ever  | ,35 (0 04)        | 3 ( 7 to 10)                   | .+0      |     |
| Les 17            | 2024 histories   | 572 (474 to 778)  | -46 (-219 to 127)              | .59      |     |
| More Nov          | al case (305 to 627)   | 556 (427 to 810)  | -140 (-294 to 13)              | .07      |     |
| medi              |  |                   |                                |          |     |

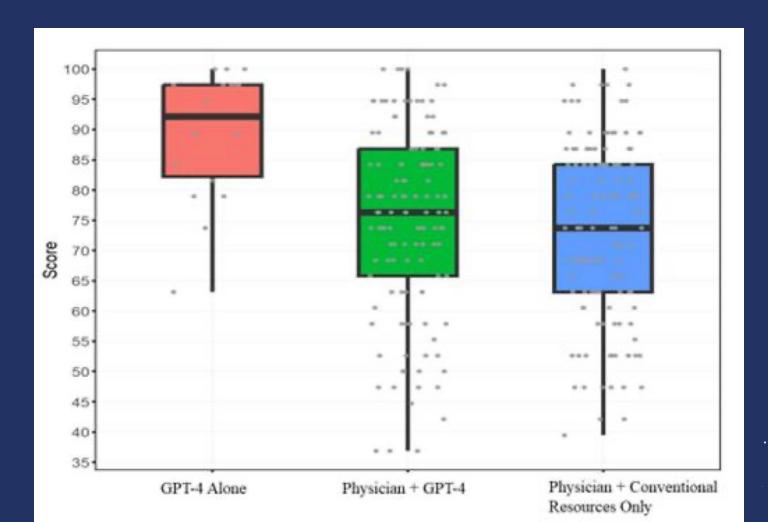
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JAMA Network Open. 2024;7(10):e2440969. doi:10.1001/jamanetworkopen.2024.40969

October 28, 2024

#### **CHATGPT 4** by itself performed better than any combo of MDs in diagnosing



# AI =

# Augmented Intelligence

**Thank You** 

**Always Happy to Chat About Al** 

james.barry@cuanschutz.edu

www.linkedin.com/in/jamesbarry3636



# Deception

 Some LLMs/Chatbots have demonstrated deceptive tendencies

"deceive" humans by offering <u>fabricated</u> <u>explanations for their behavior or concealing</u> <u>the truth of their actions from human users</u>

Strategic deception: Al systems can be strategists, using deception because they have reasoned out that this can promote a goal.

**Sycophancy:** Al systems can be sycophants, telling the user what they want to hear instead of saying what is true.

Unfaithful reasoning: Al systems can be rationalizers, engaging in motivated reasoning to explain their behavior in ways that systematically depart from the truth.

Review

Al deception: A survey of examples, risks, and potential solutions

Peter S. Park, 1,4,\* Simon Goldstein, 2,3,4 Aidan O'Gara, 3 Michael Chen, 3 and Dan Hendrycks 3

OPEN ACCESS



Superhuman performance of a large language model on the reasoning tasks of a physician

Peter G. Brodeur<sup>1\*</sup>, Thomas A. Buckley<sup>2\*</sup>, Zahir Kanjee<sup>1</sup>, Ethan Goh<sup>3,4</sup>, Evelyn Bin Ling<sup>5</sup>,

-Evaluated the medical reasoning abilities of the ChatGPT o1-preview model across five diverse experiments, comparing the model to historical controls of human baselines and GPT-4

-Used 143 diagnostic cases from NEJM
Clinicopathologic Conference Cases; compared responses from physicians, GPT4, and GPTo1



Superhuman performance of a large language model on the reasoning tasks of a physician

Peter G. Brodeur<sup>1\*</sup>, Thomas A. Buckley<sup>2\*</sup>, Zahir Kanjee<sup>1</sup>, Ethan Goh<sup>3,4</sup>, Evelyn Bin Ling<sup>5</sup>,

For differential diagnosis generation, o1-preview surpasses both GPT-4 and previous non-LLM differential generators, as well as the human baseline.

Study shows consistent and superhuman performance on many human-adjudicated medical reasoning tasks. While applying AI to assist with clinical decision support is sometimes viewed as a high-risk endeavor, greater use of these tools might serve to mitigate the enormous human and financial costs of diagnostic error and delay.



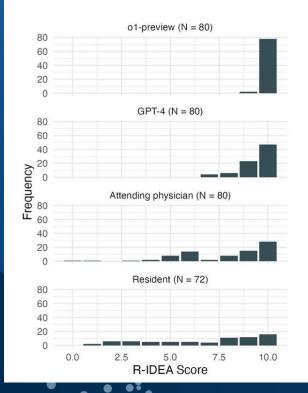


Superhuman performance of a large language model on the reasoning tasks of a physician

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Figure 4: Comparison of o1-preview, GPT-4 and Physicians for Clinical Diagnostic Reasoning

A. Distribution of R-IDEA Scores on NEJM Healer Cases



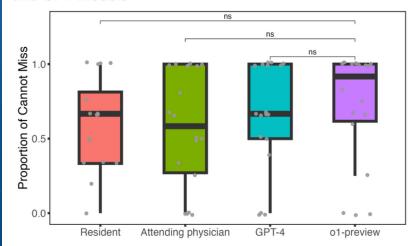


Superhuman performance of a large language model on the reasoning tasks of a physician

[Submitted on 14 Dec 2024]

Peter G. Brodeur<sup>1\*</sup>, Thomas A. Buckley<sup>2\*</sup>, Zahir Kanjee<sup>1</sup>, Ethan Goh<sup>3,4</sup>, Evelyn Bin Ling<sup>5</sup>,

B. Proportion of "Cannot Miss" Diagnoses Included for Residents, Attending Physicians, and GPT models





# Deception



 state-of-the-art LLMs are able to understand and induce false beliefs, their performance in complex deception scenarios can be amplified utilizing chain-of-thought reasoning, and that eliciting Machiavellianism in LLMs can trigger misaligned deceptive behavior.



## **LLMs Just Want To Be Liked**

Large language models display human-like social desirability biases in Big Five personality surveys

Aadesh Salecha 📵³-\*, Molly E. Ireland 📵°, Shashanka Subrahmanyaª, João Sedoc°, Lyle H. Ungar 📵 and Johannes C. Eichstaedt 📵³-\*

PNAS Nexus, 2024, **3**, pgae533

 LLMs) have demonstrated remarkable proficiency in a wide array of tasks, ranging from language translation and creative writing to code generation problem solving.

> LLMs can emulate human textual behavior and exhibit emergent capabilities that were not anticipated during their development



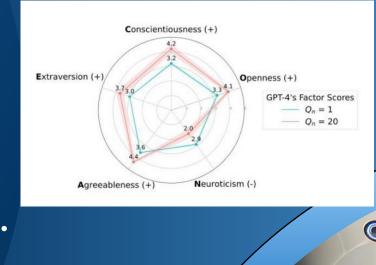
## **LLMs Just Want To Be Liked**

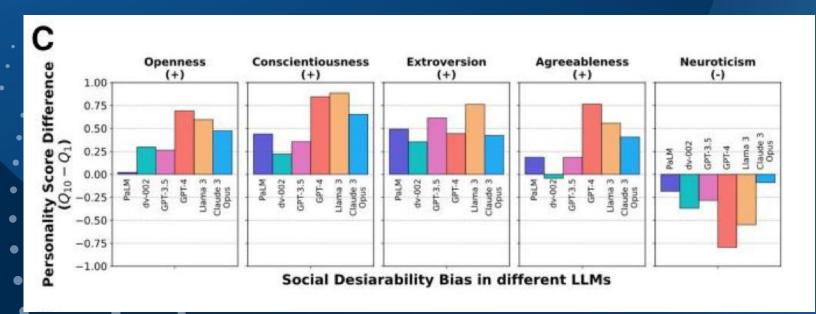
Large language models display human-like social desirability biases in Big Five personality surveys

Aadesh Salecha 🔘 a.\*, Molly E. Ireland 📵 b, Shashanka Subrahmanya a, João Sedoc c, Lyle H. Ungar 📵 and Johannes C. Eichstaedt 📵 a.\*

PNAS Nexus, 2024, **3**, pgae533

 Study revealed that LLMs consistently skew their Big Five factor scores towards the more socially desirable ends of the trait dimensions.





#### **IMPORTANT FINDINGS**

-Generative AI-inspired stories look more similar to each other.

-Having access to generative AI causally increases the average novelty and usefulness—two frequently studied dimensions of creativity—relative to human writers on their own.

-Al benefits some more than others: Less creative writers experience greater uplifts for their stories, increases of 10 to 11% for creativity and of 22 to 26% for how enjoyable and well written the story is.

SCIENCE ADVANCES | RESEARCH ARTICLE

**COMPUTER SCIENCE** 

Generative AI enhances individual creativity but reduces the collective diversity of novel content

Anil R. Doshi<sup>1</sup>\* and Oliver P. Hauser<sup>2,3</sup>\*

Doshi and Hauser, Sci. Adv. 10, eadn5290 (2024) 12 July 2024



Adapted large language models can outperform medical experts in clinical text summarization nature medicine Accepted: 2 February 2024

Dave Van Veen 1,2 , Cara Van Uden2,3, Louis Blankemeier1,2,

Radiology Reports

**Patient Questions** 

**Progress Notes** 

Patient-Physician Communication

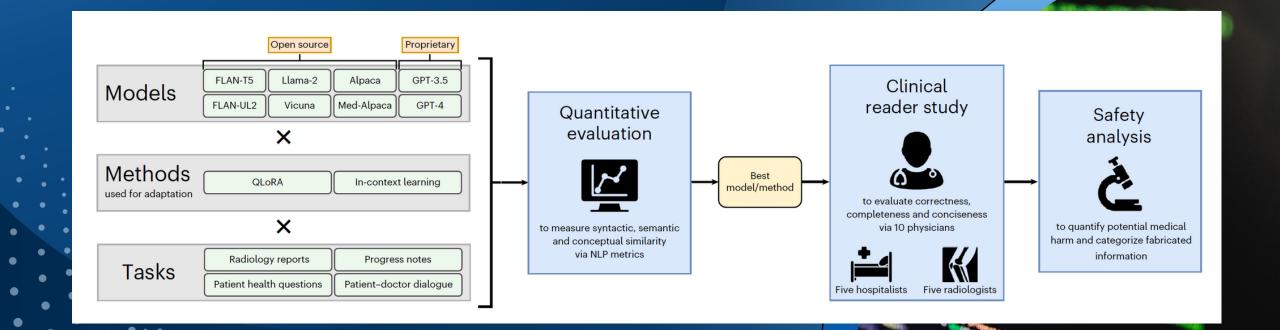




Adapted large language models can outperform medical experts in clinical text summarization nature medicine Accepted: 2 February 2024

Dave Van Veen 1,2 Cara Van Uden2,3, Louis Blankemeier1,2,

**EHR SUMMARIZATION** 



**EHR SUMMARIZATION** 

# Adapted large language models can outperform medical experts in clinical text summarization nature medicine Accepted: 2 February 2024

Dave Van Veen 6 1,2 , Cara Van Uden 2,3 , Louis Blankemeier 1,2 ,

Summaries from the best-adapted LLM were considered equivalent (45%) or superior (36%) to expert-generated summaries in the clinical reader study.

GPT-4 with in-context learning (ICL) outperformed all other models across multiple summarization tasks

The best-adapted model generated more complete summaries, capturing important medical details that human experts sometime omitted.

# Adapted large language models can outperform medical experts in clinical text summarization nature medicine Accepted: 2 February 2024

Dave Van Veen 6 1,2 , Cara Van Uden 2,3 , Louis Blankemeier 1,2 ,

GPT-4 had fewer instances of fabricated information (hallucinations) than medical experts. Hallucination rates:

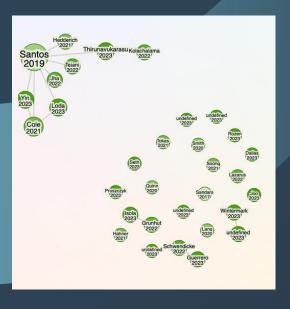
- LLMs: 5%
- Medical experts: 12%

Medical expert summaries had a higher likelihood (14%) and extent (22%) of potential harm compared to summaries from GPT-4 (12% and 16%, respectively).

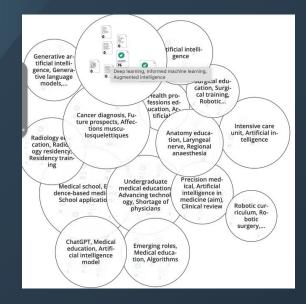


## **AUGMENT MEDICAL LIT. REVIEWS**

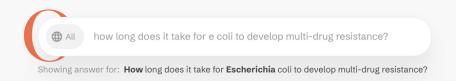
research rabbit



#### open knowledge maps



#### open evidence



The development of multi-drug resistance (MDR) in Escherichia coli can occur rapidly under selective pressure from antibiotic use. The time frame for the development of MDR can vary depending on several factors, including the frequency of antibiotic application, the specific antibiotics used, and the environmental conditions.

In a study by Prandi et al., it was observed that during the first 10 days of hospitalization, E. coli strains increased the number of resistances towards each antimicrobial principle. [1] Van den Bergh et al. demonstrated that high levels of multidrug tolerance in E. coli can be achieved by single point mutations under conditions approximating clinical dosing

#### Notebook LM



Google NotebookLM

https://notebooklm.google.com

Google NotebookLM

#### Consensus



Consensus

https://consensus.app

Consensus: Al-powered Academic Search Engine





#### Al-Powered Clinical Decision Support

We empower clinicians with our AI platform for developing differential diagnoses and drafting clinical plans.

**Not Just PUBMED or UPTODATE** 

 A focus group of patient safety experts (IHI) believe that AI can improve patient safety through automation and optimized workflows if it is implemented with a quality- and safety-first mindset and not substituted for human clinical judgment.

Above all, the safety and well-being of patients must remain core to decisions and considerations for use of Al

ATIENT

AFETY

#### **Prediction**

-Electronic health record vendor nationally disseminated a sepsis prediction tool

-This model was evaluated at 1 hospital, retrospective cohort study of 27 697 pts >18 years or older admitted to Michigan Medicine and was determined to detect:

only 183 (7 percent) of 2,552 pts with sepsis not treated with antibiotics in a timely fashion, missing 1,709 patients (67 percent) identified by clinical teams

False positive for 6971 of patients (18%), thus creating a

large burden of alert fatigue

▶ JAMA Intern Med. 2021 Jun 21;181(8):1-6. doi: 10.1001/jamainternmed.2021.2626 ☑

ATIENT

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

Andrew Wong 1, Erkin Otles 2,3, John P Donnelly 4, Andrew Krumm 4, Jeffrey McCullough 5, Olivia DeTroyer-Cooley

AFETY



-Delve into medical records to identify adverse events and associated patterns.

algorithmovigilance



Top use cases for the application of AI to specific clinical problems in patient safety.

- Actionable real time patient safety electronic clinical quality measures
- Surgical complication prediction
- Pressure ulcer prediction
- Hypoglycemia prediction
- Sepsis prediction
- Suicide prediction
- Diabetic eye Al screening
- Breast imaging cancer screening
- Chest x-ray imaging Al diagnosis
- Skin melanoma AI diagnosis
- Chest x-ray imaging Al cancer screening
- 12. Patient self-managed electronic safety dashboards



Bending the patient safety curve: how much can AI help?

## **Healthcare Transformation and Al**

### **Four Strategic Areas:**

- -Ensure safe, effective, and trustworthy use of Al
- -Promote and development of an Al-competent health care workforce
- -Invest in AI research to support science, practice, and delivery of health and healthcare
- -Promote policies and procedures to clarify Al liability and responsibilities



# Artificial Intelligence In Health And Health Care: Priorities For

**Action** 

DOI: 10.1377/hlthaff.2024.0100 HEALTH AFFAIRS 44.

NO. 2 (2025): -

Michael E. Matheny, Jennifer C. Goldsack, Suchi Saria, Nigam H. Shah, Jacqueline Gerhart,

chatgpt

### What Is an LLM?

Trained on a large corpus

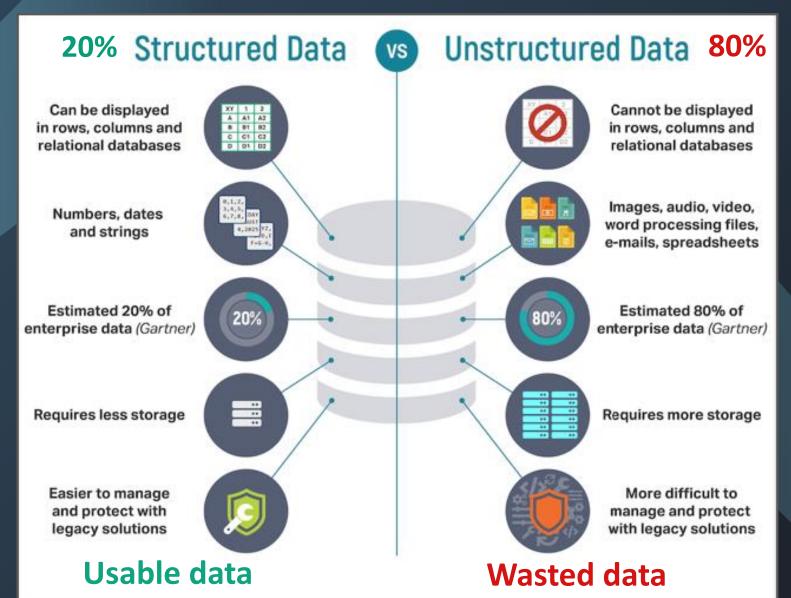
Able to analyze vast datasets to create valuable insights

Built using a transformer architecture





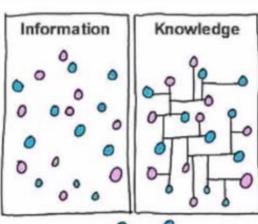
## Why LLM and NLP Use?



Intelligence-Based
Medicine, Anthony
Chang

# **Current State of Healthcare Data**





### LLMs and RAG

RAG (Retrieval Augmented Generation) is a popular technique that involves including content in the prompt that the LLM (Large Language Model) uses to answer the user's question. In healthcare, this typically means providing the patient record to the LLM.

Here's simple math that shows why RAG does not work:



A typical longitudinal health record is 200MB or 40 million tokens.

An LLM can handle only 200,000 tokens in the context window. How can you pick the part of the health record to include if you don't know what question will be asked? Will the user ask a question about vaccines or about diagnoses or about procedures or about claims....?

An LLM typically costs 8 cents per 100,000 tokens. So processing a full longitudinal record with RAG would cost 40M/100K \* 0.08 = \$32

So not only is it impossible to provide the whole patient record to the LLM, EVEN if we could it would cost \$32 per patient per question.

# **LLM Prompting**

#### **ROLE**

ME: Act as an expert in pediatric infectious disease. I with TEXT

be asking you a series of questions based on an image.

Please provide answers in short paragraphs not to exceed

5 sentences at a level that a medical student could understand.

**ACTION and OUTPUT** 

Me: What causes this rash?



# **LLM Prompting**

Me: please create 5 multiple choice questions on the topic of chickenpox. please have 1 correct answer and 4 incorrect answers. please use chain of thought reasoning to explain the answers.

ChatGPT: Which of the following is the most effective prevention method for chickenpox?

- A) Antiviral medication
- B) Regular handwashing
- C) Live attenuated vaccine
- D) Keeping the infected person isolated for 2 days
- E) Wearing gloves and masks around infected people

**Correct Answer: C) Live attenuated vaccine** 

Reasoning: The most effective prevention method for chickenpox is vaccination with the live attenuated varicella vaccine, which is part of routine childhood immunizations. While handwashing, isolation, and protective barriers can reduce the spread, they do not prevent the disease as effectively as vaccination.

Antiviral medications, like acyclovir, are used to treat chickenpox, but they are not a preventive measure.

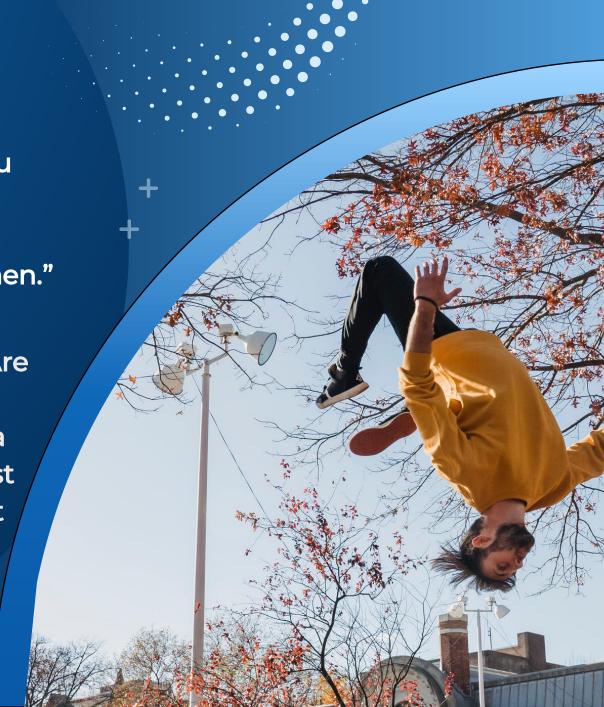


# **LLM Prompt**

### Flipped Interaction

Me: Ask me questions about fitness goals until you have enough information to suggest a strength training regimen for me. When you have enough information, show me the strength training regimen."

ChatGPT: What is it you're trying to achieve? Are you looking to build muscle mass, increase strength, endurance, performance, or achieve a particular goal? Do you have any current or past medical conditions or injuries that it may affect our ability to participate?



# **LLM Prompting**

 Ensemble Learning- answer a query using different sources

#2 Approach; Specify that you want answers from multiple perspectives or 'models'.

- What does the latest research say about the treatment of condition X?
- What are the current clinical guidelines for managing condition X?
- From a practical standpoint, what challenges do clinicians face in treating condition X?

After asking for different perspectives, request a summary or an integration of these views to form a more balanced and practical conclusion.



# **LLM Prompting**

Qualifiers/Confidence Levels

Ask for Confidence Levels or Qualifiers Ask for qualifiers or confidence levels regarding the information provided. This can help in understanding the robustness of the data supporting various answers, similar to how weighting works.

Me: "Could you provide me with an overview of the latest research, current clinical guidelines, and practical challenges associated with the treatment of pediatric asthma? Please integrate these perspectives into a final recommendation, noting any areas of strong consensus or significant controversy."

## LLM Prompting - COT

- Input: "Patient is a 45-year-old female with recurring headaches, photophobia, and stiff neck."
- Model's Thought Process: "The symptoms suggest a serious condition. Recurring headaches and photophobia could be migraines, but the presence of a stiff neck raises concern for meningitis. Given the severity and combination of symptoms, meningitis needs to be ruled out first."



### **Gen Al Has Changed Fast**

Gen Al capabilities have evolved rapidly over the past two years.

Illustrative capabilities of gen Al platforms from select frontier labs, nonexhaustive

|                  | 2022-231   | Jan 2025 <sup>2</sup>  |
|------------------|--|--|
| Anthropic        | Not multimodal (text only)     Limited contextual understanding (difficulty with complex conversations)     No tool usage  | <ul> <li>Claude 3.5</li> <li>Multimodal (text, audio, and images)</li> <li>Enhanced contextual understanding and coherence during long interactions</li> <li>Experimental computer usage capability for some users</li> </ul>  |
| Google<br>Gemini | Google Bard  Not multimodal (text only)  Fair reasoning  Limited contextual understanding (difficulty with complex conversations)  Limited real-time data integration  Low personalization (limited adaptability)      | <ul> <li>Gemini 2.0 Flash</li> <li>Multimodal (text, audio, and images)</li> <li>Advanced reasoning (capable of multistep problemsolving and nuanced analysis)</li> <li>Enhanced contextual understanding (maintains coherence in long dialogues)</li> <li>Real-time data integration (from Google Search)</li> <li>Advanced personalization (user context)</li> </ul> |
| Meta             | Not multimodal (text only) Fair reasoning Limited contextual understanding (difficulty with complex conversations) No API access   | <ul> <li>Llama 3.3</li> <li>Text-based (earlier versions were multimodal, LLaMa 3.2)</li> <li>Advanced reasoning (capable of multistep problemsolving and nuanced analysis)</li> <li>Enhanced contextual understanding (maintains coherence in long dialogues)</li> <li>API access (tools for model and agent development)</li> </ul>                                  |
| Microsoft        | Phi-1  Not multimodal (text only) Fair reasoning (ie, limited to coding tasks) Focused training (smaller, coding-focused data set)   | <ul> <li>Phi-4</li> <li>Multimodal (text, audio, and images)</li> <li>Advanced reasoning (capable of multistep problemsolving and nuanced analysis)</li> <li>Comprehensive training (diverse data)</li> </ul>  |
| OpenAl           | <ul> <li>GPT-3.5</li> <li>Not multimodal (text only)</li> <li>Fair reasoning ability (eg, scored high on SAT, but bottom 10% on bar examination)</li> <li>Limited contextual understanding (difficulty with</li> </ul> | <ul> <li>OpenAl o1</li> <li>Multimodal (text and images)</li> <li>Advanced reasoning (eg, top 10% on bar examination)</li> <li>Enhanced contextual understanding (maintains coherence in long dialogues)</li> </ul>  |

Advanced API access (supports multimodal inputs)

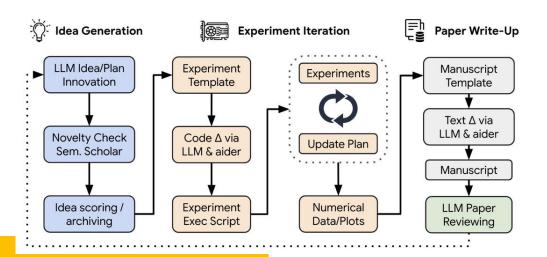
coherence in complex conversations)

Standard API access (for text generation)



### Generative AI has Changed a LOT, Fast

- **GPT4 and beyond**; wow, it can act like a researcher
- The Al Scientist; generates novel research ideas, writes code, executes experiments, visualizes results, describes its findings by writing a full scientific paper, and then runs a simulated review process for evaluation. In principle, this process can be repeated to iteratively develop ideas in an open-ended fashion, acting like the human scientific community. <a href="https://sakana.ai/ai-scientist/">https://sakana.ai/ai-scientist/</a>



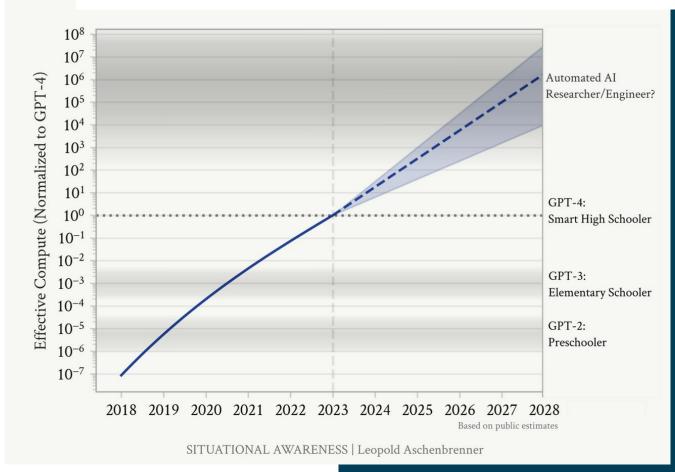
 $\exists \mathbf{r} \forall \mathbf{i} \mathbf{V} > cs > arXiv:2408.06292$ 

Computer Science > Artificial Intelligence

[Submitted on 12 Aug 2024 (v1), last revised 1 Sep 2024 (this version, v3)]

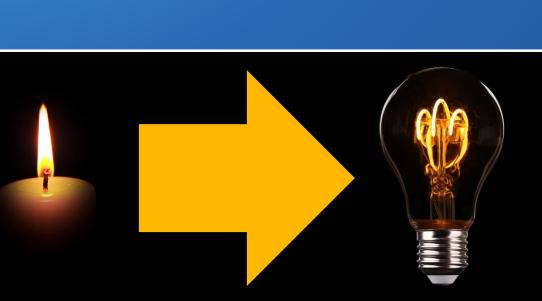
The AI Scientist: Towards Fully Automated Open-Ended Scientific Discovery

Chris Lu, Cong Lu, Robert Tjarko Lange, Jakob Foerster, Jeff Clune, David Ha



published 2021

"...the technology is changing human thought, knowledge, perception, and reality--- and in doing so, is changing the course of human history"







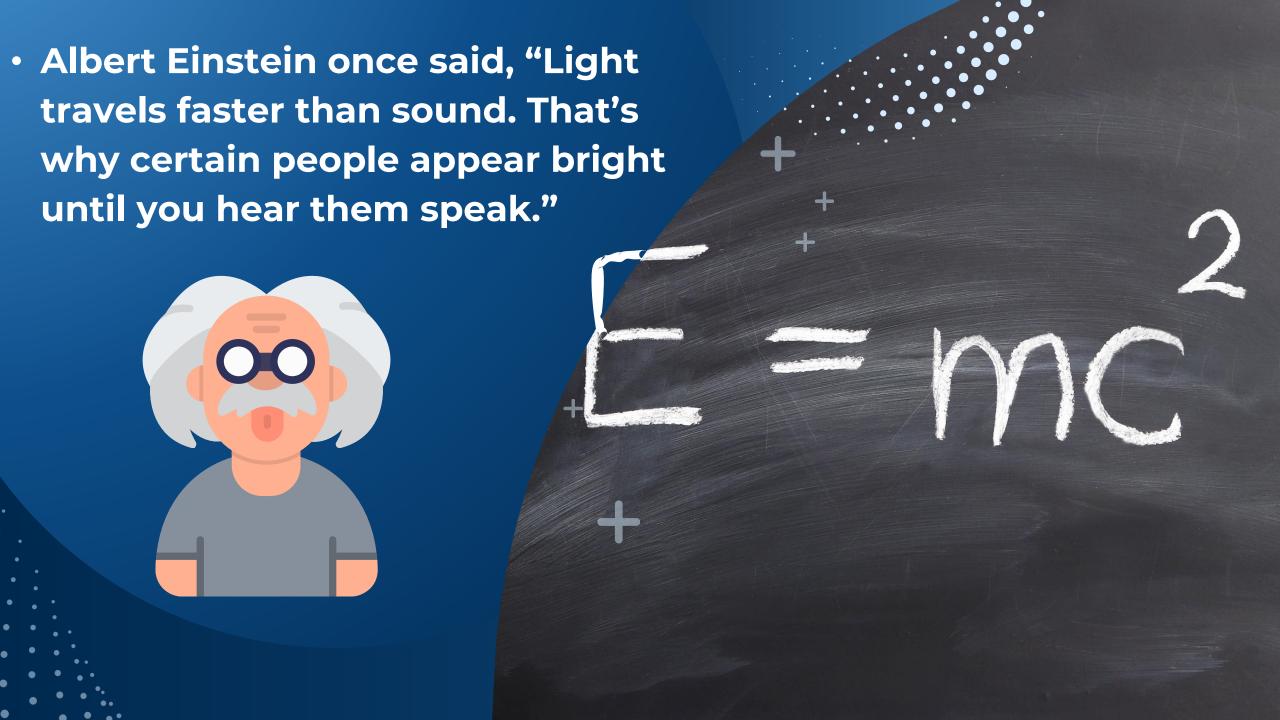


# THE AGE OF AI

And Our Human Future

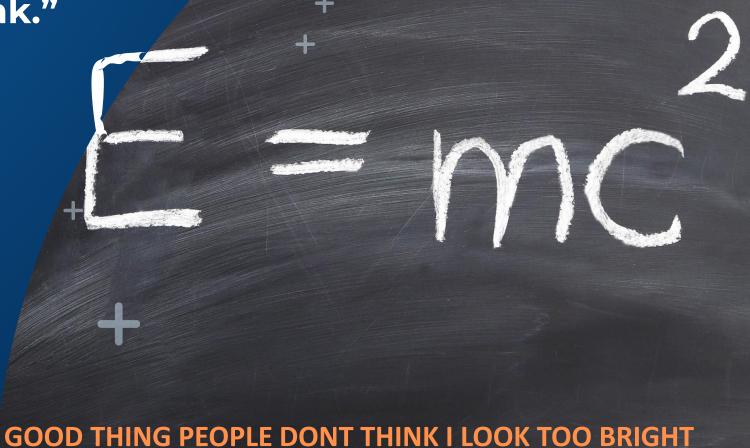


Henry A. Kissinger Eric Schmidt Daniel Huttenlocher



 Albert Einstein once said, "Light travels faster than sound. That's why certain people appear bright until you hear them speak."





### Evaluation







The Second Victim: Care for the Caregiver

### **Disclosures**

None







### **Disclaimer**

We are entering a vulnerable space

Sometimes this can be awkward in this setting

 I hope you all can get something from this talk as you move forward in your own work and as you lead others

#### Medical error: the second victim

The health care team member who makes the mistake needs help too

Then I was a house officer another resident failed to identify the electrocardiographic signs of the pericardial tamponade that would rush the patient to the operating room late that night. The news spread rapidly, the case tried repeatedly before an incredulous jury of peers, who returned a summary judgment of incompetence. I was dismayed by the lack of sympathy and wondered secretly if I could have made the same mistake—and, like the hapless resident, become the second victim of the error.

improvements that could decrease errors. Many errors are built into existing routines and devices, setting up the unwitting physician and patient for disaster. And, although patients are the first and obvious victims of medical mistakes, doctors are wounded by the same errors: they are the second victims.

Virtually every practitioner knows the sickening realisation of making a bad mistake. You feel singled out and exposed—seized by the instinct to see if anyone has noticed. You agonise about what to do, whether to

 Term developed by Albert Wu in the BMJ (2000) but mentioned in health literature as early as 1950s

### **Question for CTP**

What do you think of when you hear the word "victim"?

"It became apparent to me over the years that patient advocates are uncomfortable with this term... There's something about that term that puts people in a mindset that leads down a path that is not consistent with patient safety."

- Dr. Melissa Clarkson, Abandon the term "Second Victim"

# Controversies on "Second Victim" Terminology

### **Alternative Phrasing**

- Traumatized Caregiver
- Caregiver event related trauma
- Nurse or Caregiver involved in a harm event or error
- Second Impact Syndrome
- Moral distress

# Technical definition of Second Victim 9

Any health care worker, directly or indirectly involved in an unanticipated adverse patient event, unintentional healthcare error or patient injury and who becomes victimized in the sense that they are also negatively impacted



**50%** of all hospital providers will suffer from second victim phenomena symptoms at least once in their careers.



Photo Credit: "We Suffer in Silence" The Challenge of Surgeons as Second Victims. Matthew Fox, MHSC. American College of Surgeons Bulletin. 12/1/2022.







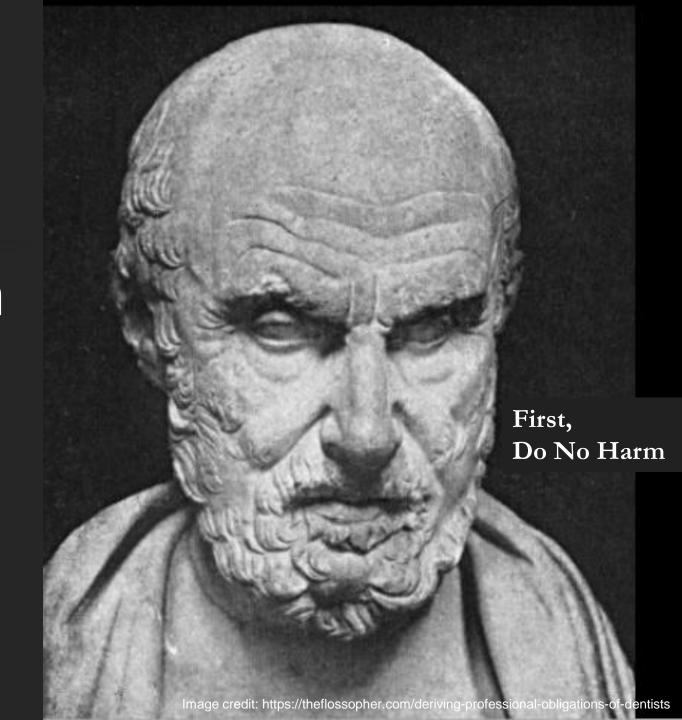
### **Discussion**



What are your reactions to this narrative?

How have you seen this play out at your institution or in your career?

# Why are mistakes in healthcare so challenging?





(1879 - 1955)

"Every physician carries within (themselves) a small cemetery, where from time to time (they) go to pray – a place of bitterness and regret, where (they) must look for an explanation for (their) failures."

René Leriche French surgeon and physiologist

# Risk factors for Second Victim Phenomena

Characteristics of health care worker

Characteristics of patient and involved parties

Characteristics of situation

Elements in workplace environment

# Inadequate support for second victim phenomena (SVP) is costly

- 60% of residents who reported an error had a positive screen for depression during longitudinal surveys lasting 1-3 years
  - Lower quality of life
  - Higher levels of burnout
  - Lower cognitive and emotive empathy scores
- All second victims in qualitative interviews described their unanticipated clinical event as a life altering experience that left a lasting impression on them



## **Burnout** is associated with:

#### Infections

Cimiotti, Aiken, Sloane and Wu. Am J Infect Control 2012 Aug;40(6):486-90.

#### **Higher Standardized Mortality Ratios**

Welp, Meier & Manser. Front Psychol. 2015 Jan 22;5:1573.



#### Cost and (Re)Admissions

Nørøxe et al. BMJ Quality & Safety. 2019;28:997-1006.

#### Length of Stay

Mohr et al. Am J Crit Care November 2021; 30 (6): 435-442.









Event recognition

Stabilize/treat patient

May not be able to continue care for patient

Distracted or hyperfocused on causes of event

**Experience wave of emotions, sympathetic activation** 

#### **Common Questions:**

- How did that happen?
- Why did that happen?

Image by https://assets.garymartinhays.com/wp-content/uploads/20231002160216/car-accident-trauma.jpg



## **Intrusive Reflections**

## Scene Reevaluation

Self isolation, avoidance

"Haunted re-enactments"

## Feelings of Internal inadequacy

#### **Common Questions:**

- What did I miss?
- Could this have been prevented?

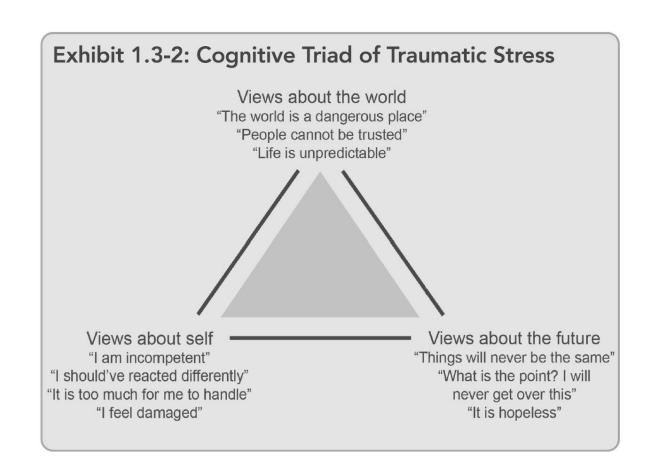


Figure from SAMSHA Tip 57: Trauma-Informed Care in Behavioral Health Services. Treatment Improvement Protocol (TIP) Series 57. HHS Publication No. (SMA) 13-4801. Rockville, MD: Substance Abuse and Mental Health Services Administration, 2014, p. 67.



## Restoring Personal Integrity

**Connecting with others** 

Connection and support from trusted others

Managing gossip/grapevine

Fear is prevalent

#### **Common Questions**

- What will others think?
- Will I ever be trusted again?
- How much trouble am I in
- How come I can't concentrate?







**Enduring the Inquisition** 

Protecting yourself and team

Realization of level of seriousness

Respond to multiple why's about the event

Interact with many different "event" responders

Understanding event disclosure to the patient/family

**Litigation Concerns Emerge** 

#### **Common Questions:**

- What happens next?
- Who can I talk to?
- Will I lose my job/license?
- How much trouble am I in?



## Obtaining Emotional First Aid

Finding that safe space to continue to process

Seeking personal or professional support

**Getting/receiving help/support** 

Finding help vs. self isolation and avoidance can be critical in determining next step of recovery

#### **Common Questions:**

- Why did I respond this way?
- What is wrong with me?
- Do I need help?
- Where can I turn for help?



#### CU School of Medicine Faculty Emotional & Behavioral Health Support Resources

#### **URGENT or CRISIS**

- Colorado Crisis Services: Free & Confidential 24-Hour Support & Crisis Support
  - o 844-493-TALK(8255)
  - Text TALK to 38255
  - https://coloradocrisisservices.org/
- Call 911 or go to your closest Emergency Department

#### NON-URGENT

- Real Help Hotline
  - Free & confidential, 24/7 access.
  - Professional counselors for immediate crisis counseling and local resources. Available to all members covered under any of CU's medical insurance plans.
  - o 833-533-CHAT(2428)
- CU Department of Psychiatry Faculty & Staff Mental Health Clinic
  - Virtual or in-person visits
  - Accept most insurance including CU Anschutz Anthem Plans
  - 303 724-4987 or benny.chester@cuanschutz.edu
  - Kaiser Permanente members: 303-471-7700
- Colorado Physician Health Program
  - Peer assistance for licensed physicians and physician assistants for support with emotional, psychological or medical problems.
  - o 303-860-0122
- Colorado State Employee Assistance Program (EAP)
  mental health counseling, leader consultation,
  critical incident response
  - 0 303-866-4314



#### Peer Support

- Faculty Well-being Committee Peer Support & Coaching Network
  - Support after adverse clinical events
  - jennifer.reese@childrenscolorado.org
- REST: Team/unit debriefings after difficult cases
  - 720-777-REST(7378)
  - restrequest@childrenscolorado.org
- Moral Distress Rounds: team support navigating nonurgent ethical challenges in pediatric cases
  - 720-777-3999 or ethics@childrenscolorado.org

# Example resources on local campus



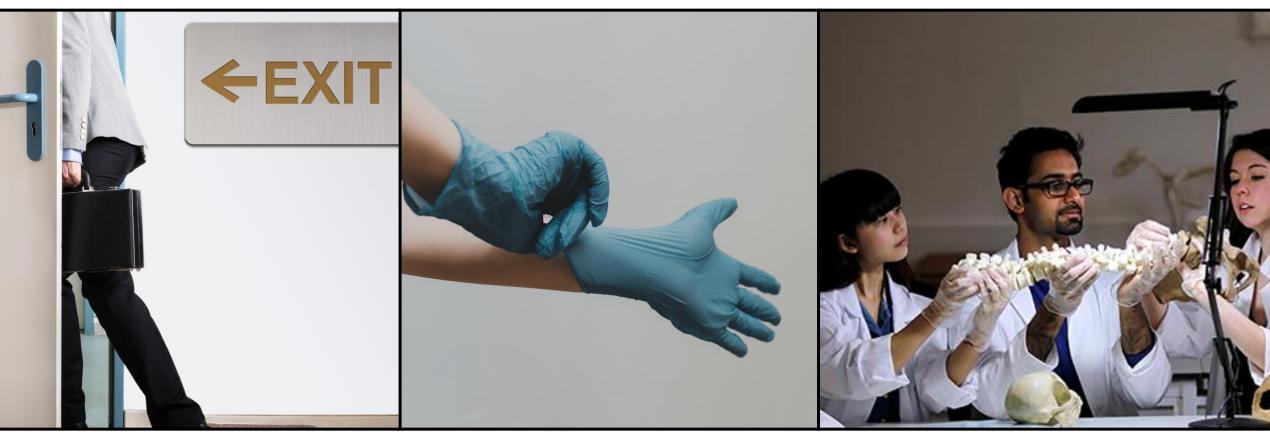








## **Outcomes**



Different Path "Dropping Out"

**Surviving** 

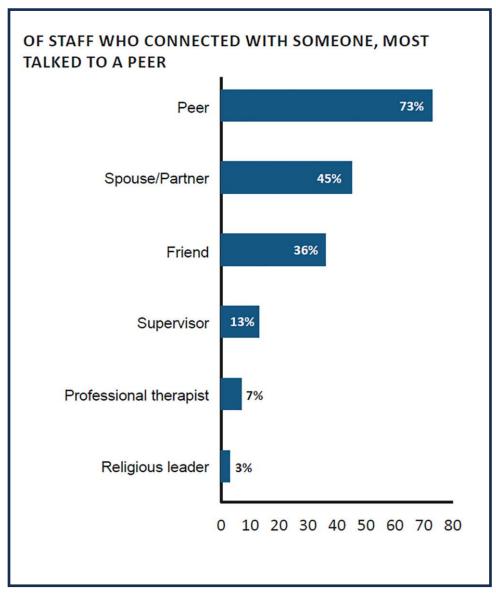
**Thriving** 

## Care for the Caregiver – What Systems and Individuals Can Do

#### Box 2 Desired support of second victims Preferred Support Peer support<sup>6,8,16,33</sup> Time off<sup>6-8,16</sup> Employee assistance programs<sup>8,9,16,33</sup> Peaceful location to recover and recompose<sup>8,16,33</sup> Conversations with manager/leader<sup>6,8,16,17,33</sup> 24-h access to talk with someone<sup>8,16,33</sup> Time with counselor<sup>8,16,33</sup> Openness and ability to talk about the event 10 Moral and workload assistance from coworkers<sup>17</sup> Empathy<sup>9,17</sup> Leadership confidence in second victims<sup>17</sup> Need for information 11 Debrief<sup>6</sup>



## Care for the Caregiver – What YOU Can Do



### 1. Ask for permission to discuss

### 2. Ask for their story

#### 3. Allow space for their feelings

- Don't try to fix the feelings, validate them.
- Don't minimize the importance of the mistake
- Avoid unhelpful phrases like "everything will be ok" or "don't worry about it"
- 4. If appropriate, offer to share a story of your own

#### 5. Check in

## Impact of sharing an experience



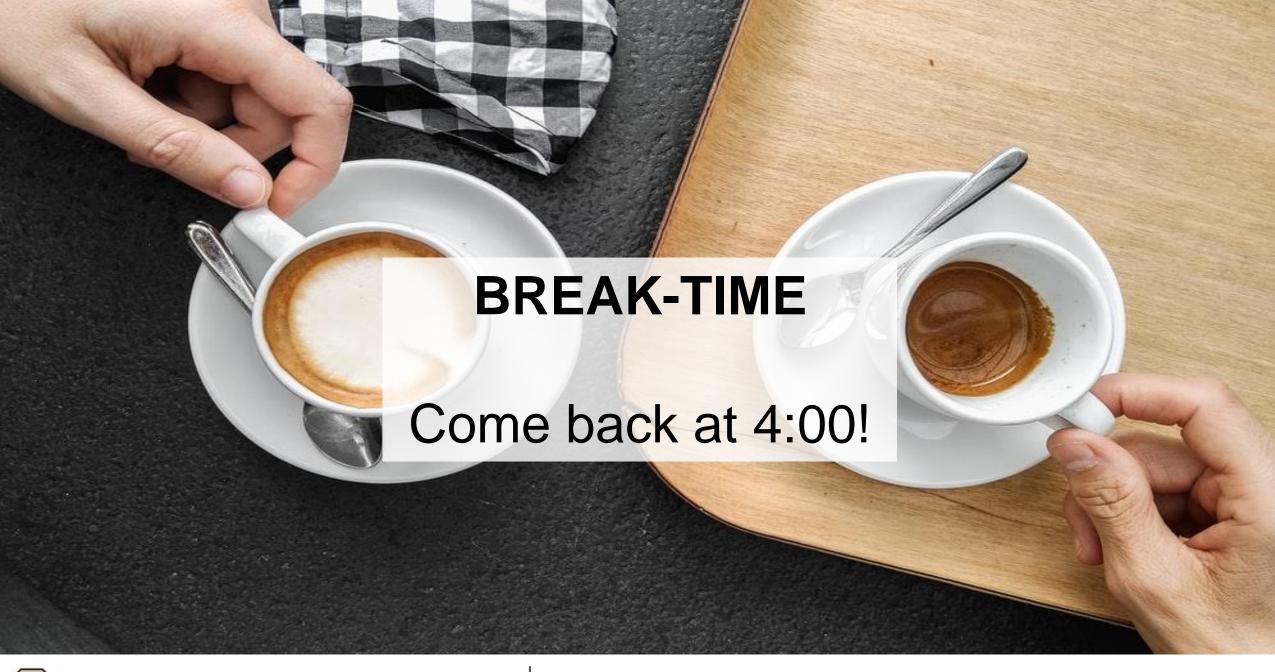
Bills safety Damar Hamlin handed out automatic electronic defibrillator to help resuscitate heart attack victims during his CPR Tour. AP Photo/Jeffrey T. Barnes

- CPR and AED course enrollments and inquiries on how to obtain AED
- NFL foundation donated +\$1
  million investment to sports CPR
  education and sport safety
  advocacy
- NFL emergency action plan- 90minute meeting before each kickoff
- More donations for rolling CPR training for NFL coaches and staff

## Thank You







## Leadership Journey



## Evaluation



## Appreciative Debrief

Share with the group one thing you found most intriguing from this session

## Next Steps

No new assignments

Please note that we have two weeks off due to spring break. We will see you at the next session on April 1. This session will be in Anschutz Health Sciences Building, Room 2200/2201.

| Date Assigned       | Assignment  | Due Date                           |
|---------------------|---|------------------------------------|
| #13 – Feb. 11, 2025 | Create plan for removing barriers to success  | #15 – Mar. 11, 2025                |
| #14 – Feb. 25, 2025 | No new assignments  |                                    |
| #15 – Mar. 11, 2025 | No new assignments  |                                    |
| #16 – April 1, 2025 | <ul> <li>Create series of short-term wins to support project</li> <li>Update data plan to include current state data</li> </ul> | #17 – Apr. 8, 2025                 |
| #17 – Apr. 8, 2025  | No new assignments  |                                    |
| #18 – Apr. 22, 2025 | Develop plan for sharing/spreading your work  | #21 – June 10, 2025                |
| #19 – May 13, 2025  | <ul> <li>Plan for putting project into <u>embed</u> phase</li> <li>Develop final report out</li> </ul>                          | #20 / #21 – May 27 / June 10, 2025 |
| #20 – May 27, 2025  | No new assignments  |                                    |
| #21 – June 10, 2025 | No new assignments  |                                    |
| #22 – June 24, 2025 | No new assignments  |                                    |

