Artificial Intelligence and Healthcare Impact

Brent Myers, MD MPH
Chief Medical Officer, ESO

Brandon Martinez
Chief Innovation Officer, ESO

Topics For Our Consideration

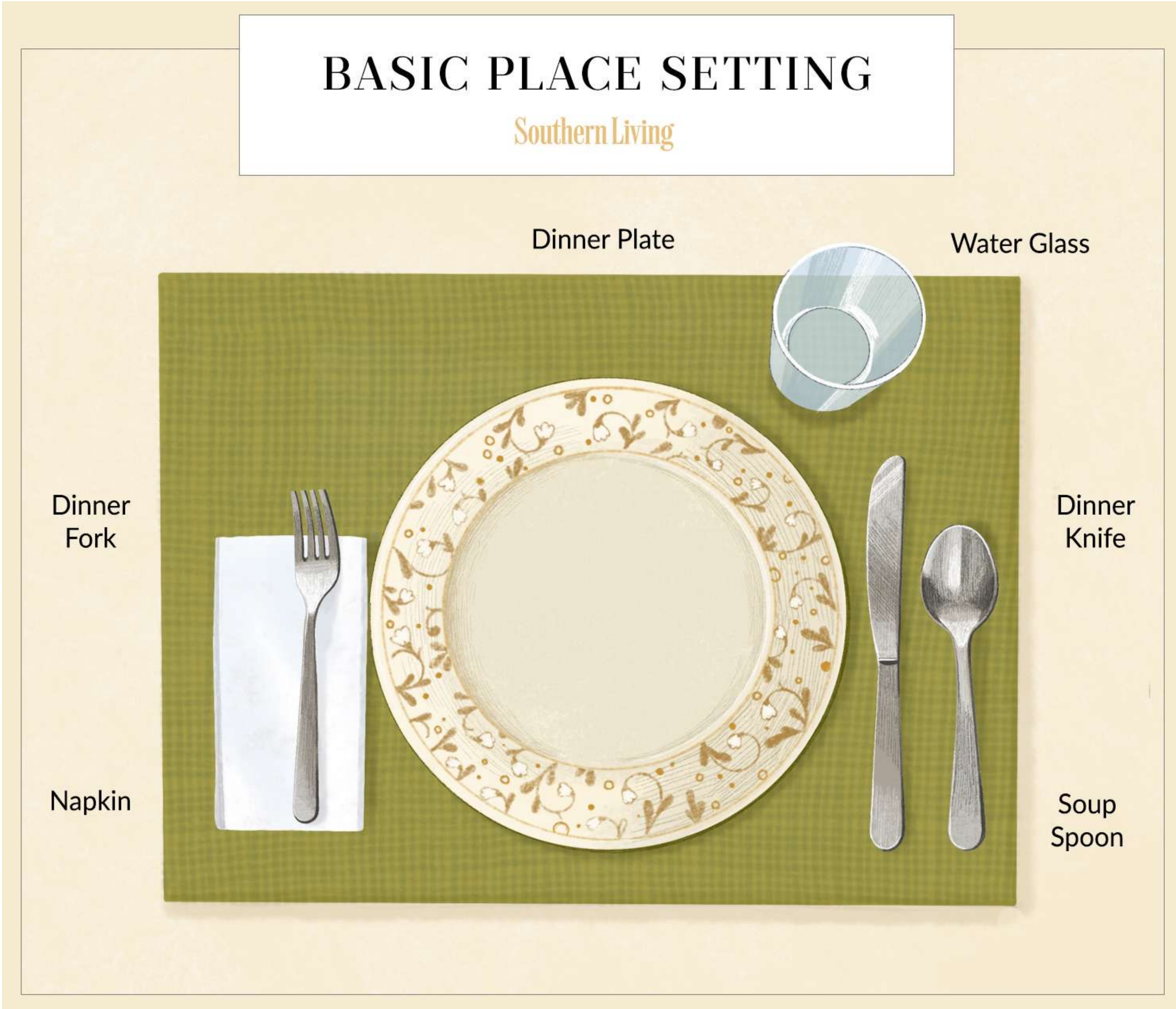
- Setting the table
- Changes for the educator
- Changes for the student
- Changes for the practice of EMS
- The way forward

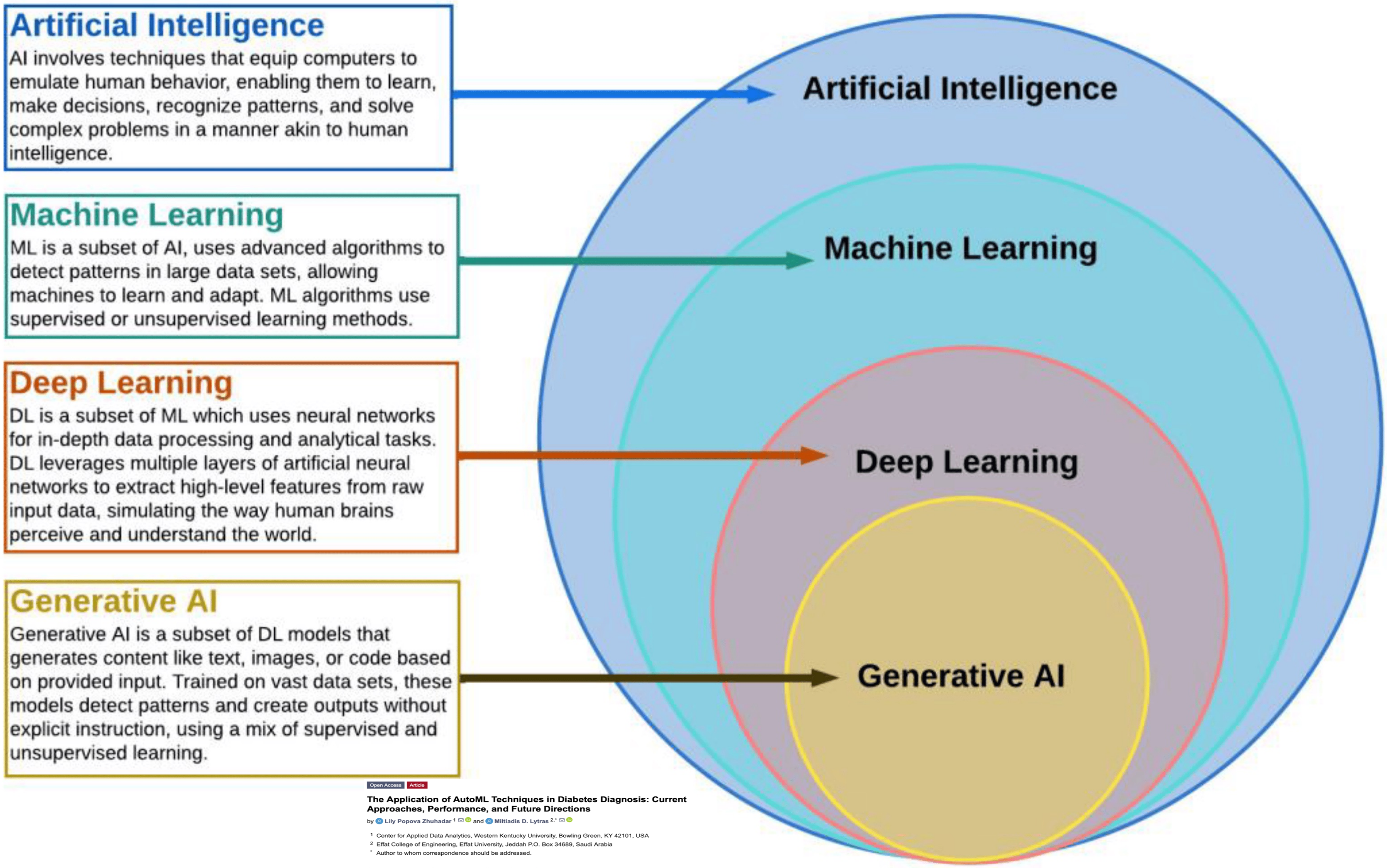
Learning Objectives

- Distinction between artificial intelligence, machine learning, neural networks, and generative AI
- Benefits and risks of AI generated individual learning plans
- Potential use of AI in EMS clinical care that will influence educational content
- External factors that may accelerate or limit the implementation of AI

This is not the first era in which Americans have held widely divergent views on important areas of morality, ethics, law, and public policy. And it is not the first time that these disagreements have seemed so important, and their airing so dangerous, that something had to be done. But now, as before, the First Amendment keeps the government from putting its thumb on the scale.

Appeal from the US District Court, Northern Florida, Number 22-13135


BASIC PLACE SETTING
Southern Living
Dinner Plate
Water Glass
Dinner Fork
Dinner Knife
Napkin
Soup Spoon



Open Access Article

The Application of AutoML Techniques in Diabetes Diagnosis: Current Approaches, Performance, and Future Directions

by Lily Popova Zhuhadar [1] and Miltiadis D. Lytras [2,*]

[1] Center for Applied Data Analytics, Western Kentucky University, Bowling Green, KY 42101, USA
[2] Effat College of Engineering, Effat University, Jeddah P.O. Box 34689, Saudi Arabia
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Sustainability **2023**, *15*(18), 13484; https://doi.org/10.3390/su151813484

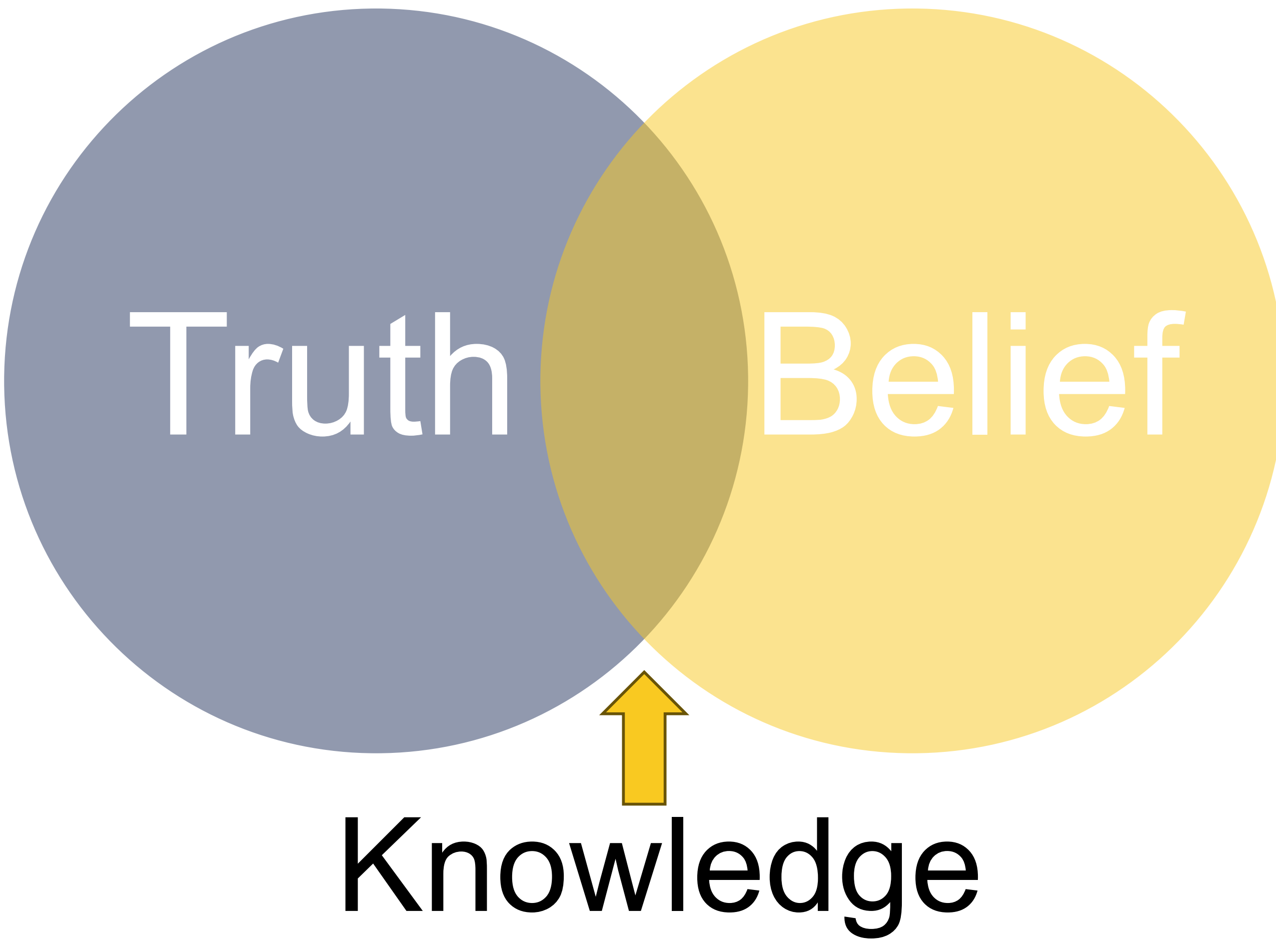
Submission received: 19 May 2023 / Revised: 28 August 2023 / Accepted: 4 September 2023 / Published: 8 September 2023

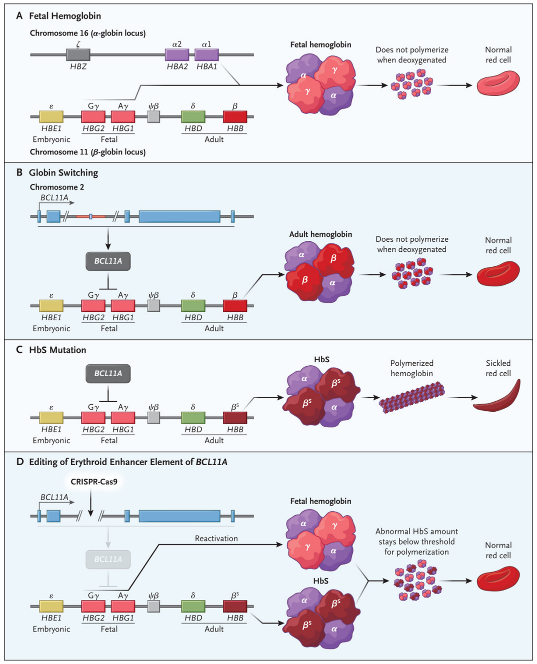
Put The Fish on the Table

Epistemology

Truth

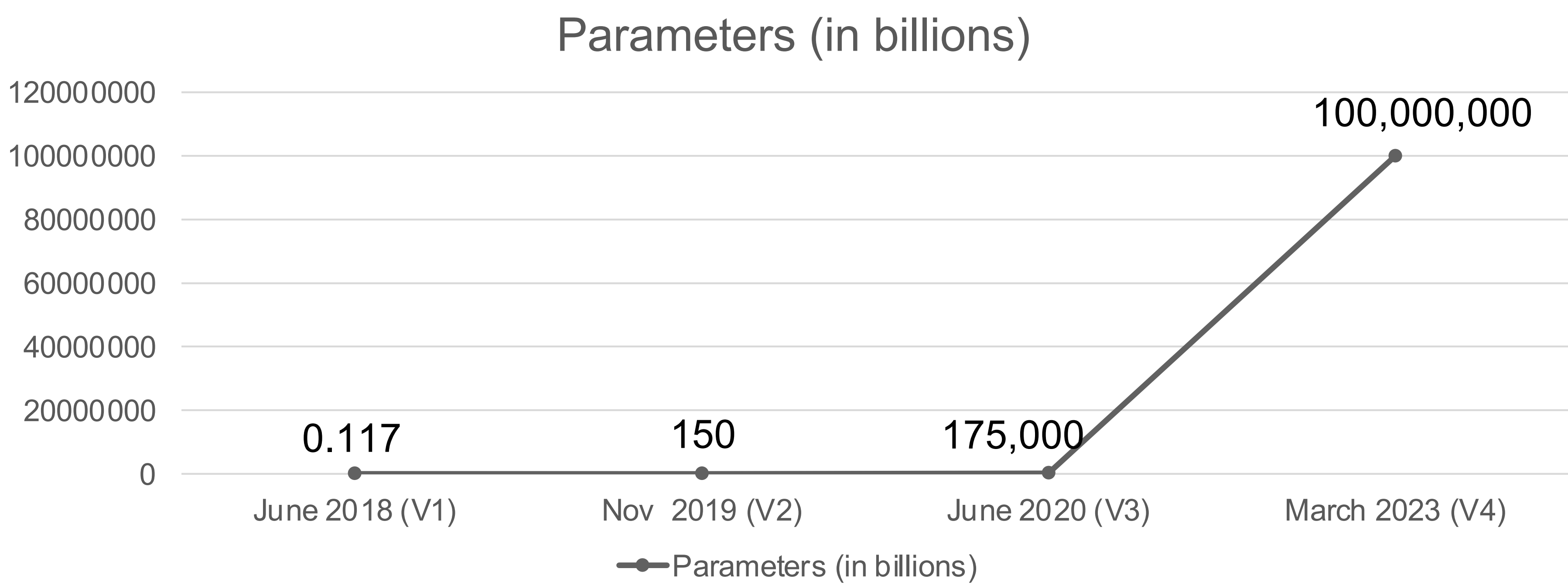
Belief


Truth
Belief
Knowledge

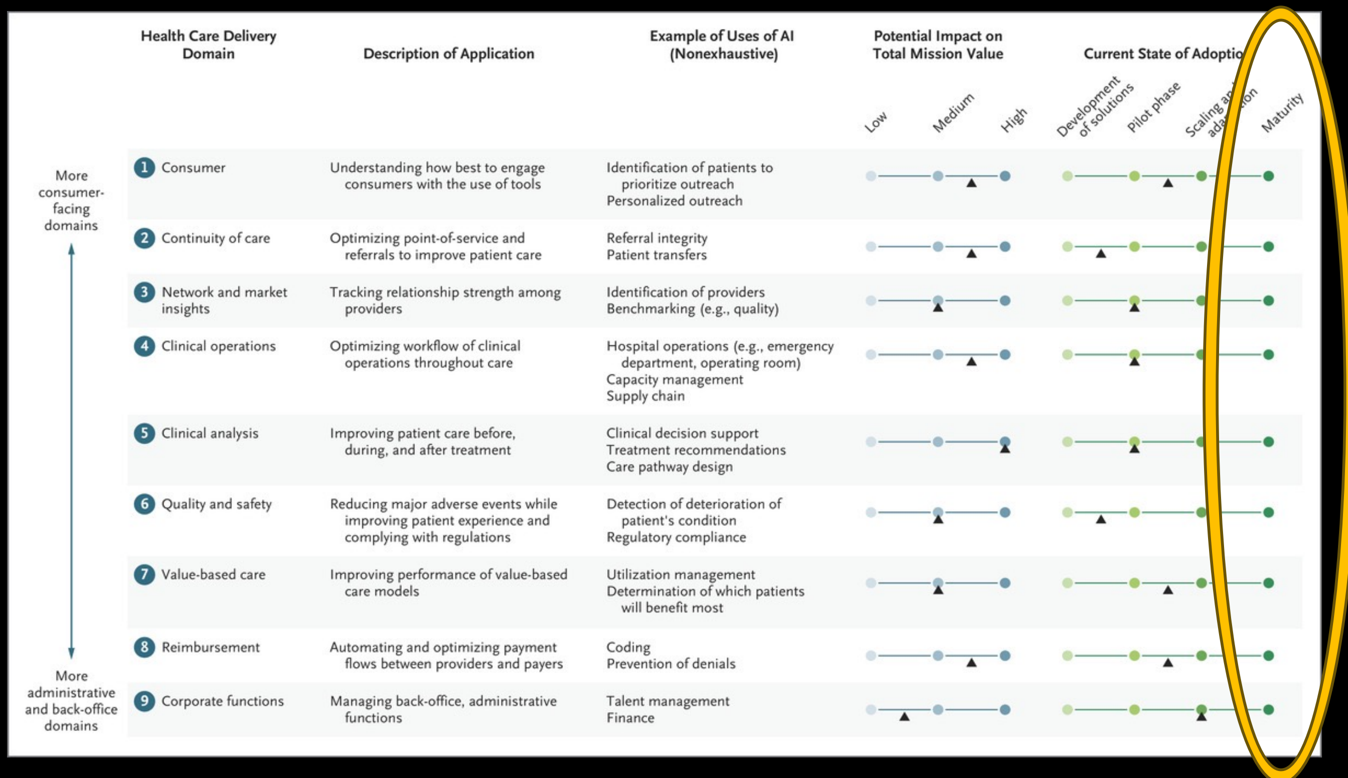


Pace of Knowledge Acquisition

Growth of Chat GPT

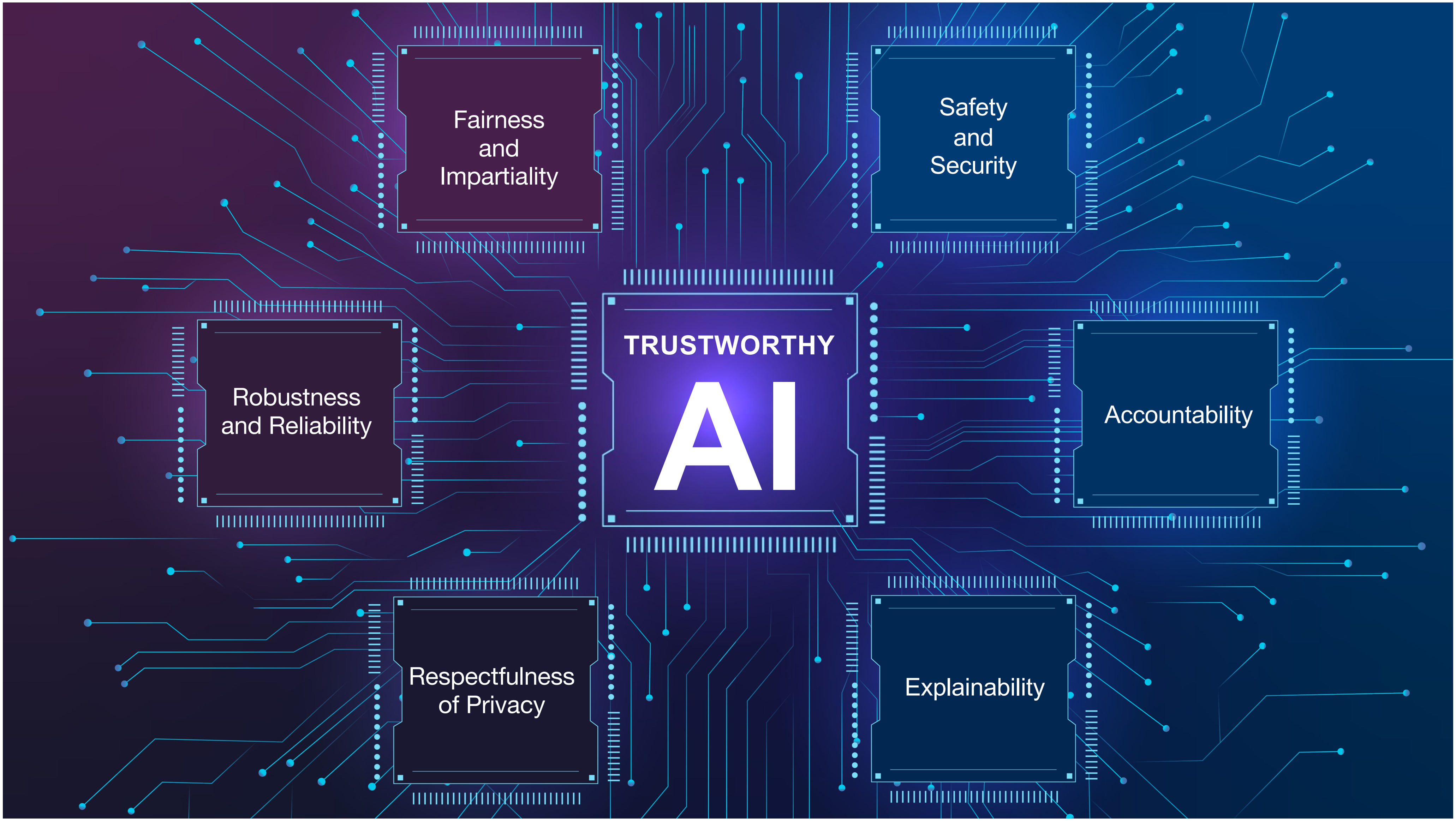


Examples of the Use of Artificial Intelligence (AI) in Health Care Delivery Domains.



NR Sahni, B Carrus. N Engl J Med 2023;389:348-358.

The NEW ENGLAND JOURNAL of MEDICINE



https://www.nist.gov/trustworthy-and-responsible-ai

Open-Access vs. Enterprise Controlled AI

- **Open-Access AI** (e.g., ChatGPT, Gemini, DeepSeek) refers to models that are broadly accessible via public APIs or web interfaces, often trained on general internet data as well as the data you feed to the model over time.

- **Enterprise-Controlled AI** (e.g., Azure GenAI, AWS Bedrock) refers to models deployed within an organization's infrastructure, with strict security, compliance, and data governance controls.

Enterprise-Grade Security, Data Residency & Sovereignty and Data Leakage Risks must be considered when evaluating and adopting AI models


EMS INSTRUCTOR

The New York Times

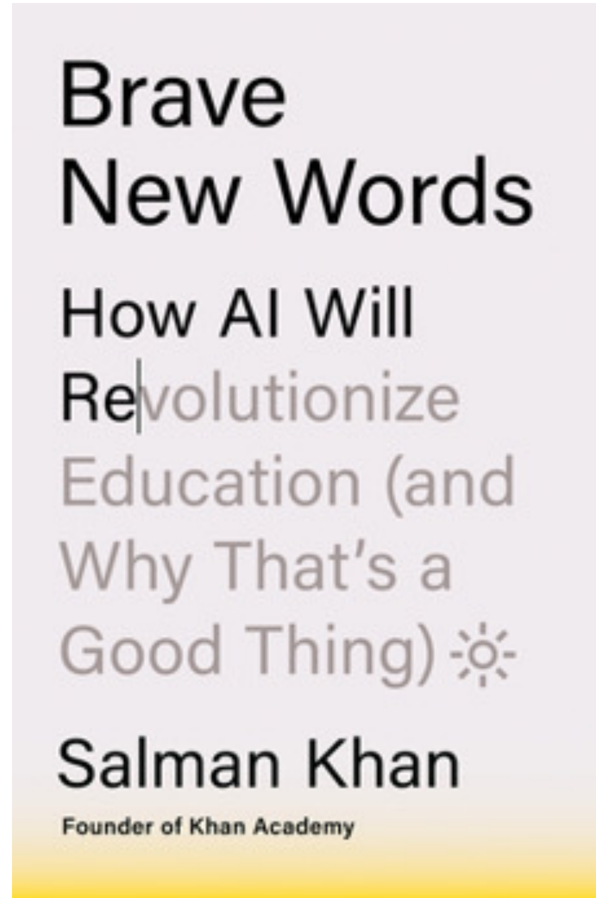
By Natasha Singer
Natasha Singer traveled to Walla Walla, Wash., for this article.

Aug. 24, 2023

Despite Cheating Fears, Schools Repeal ChatGPT Bans

Some districts that once raced to block A.I. chatbots are now trying to embrace them.

Khan Academy



TheUpshot

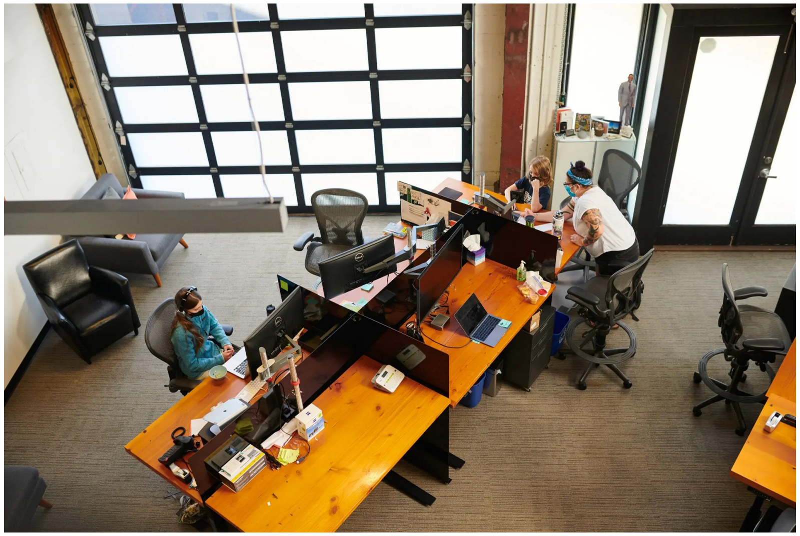
Private Tutors, Pop-Up Schools or Nothing at All: How Employers Are Helping Parents

Benefits depend on where people work, and the kind of job they have, a new survey finds, highlighting disparities that predate the pandemic.

Share full article 81

By Claire Cain Miller

Sept. 17, 2020



Chat GPT 4

- Provides individually-paced learning
- Can be set to provide graduated degrees of support/hints
- Possibly best for foundational topics

Personalized Learning & AI Automation for Educators

Intelligent Tutoring Systems

Automated Grading and Assessments

Chatbots / Assistants (Virtual TA)

Curriculum Planning

Learning Analytics

Content Recommendation

Changes for the Student

BECKER'S HEALTH IT

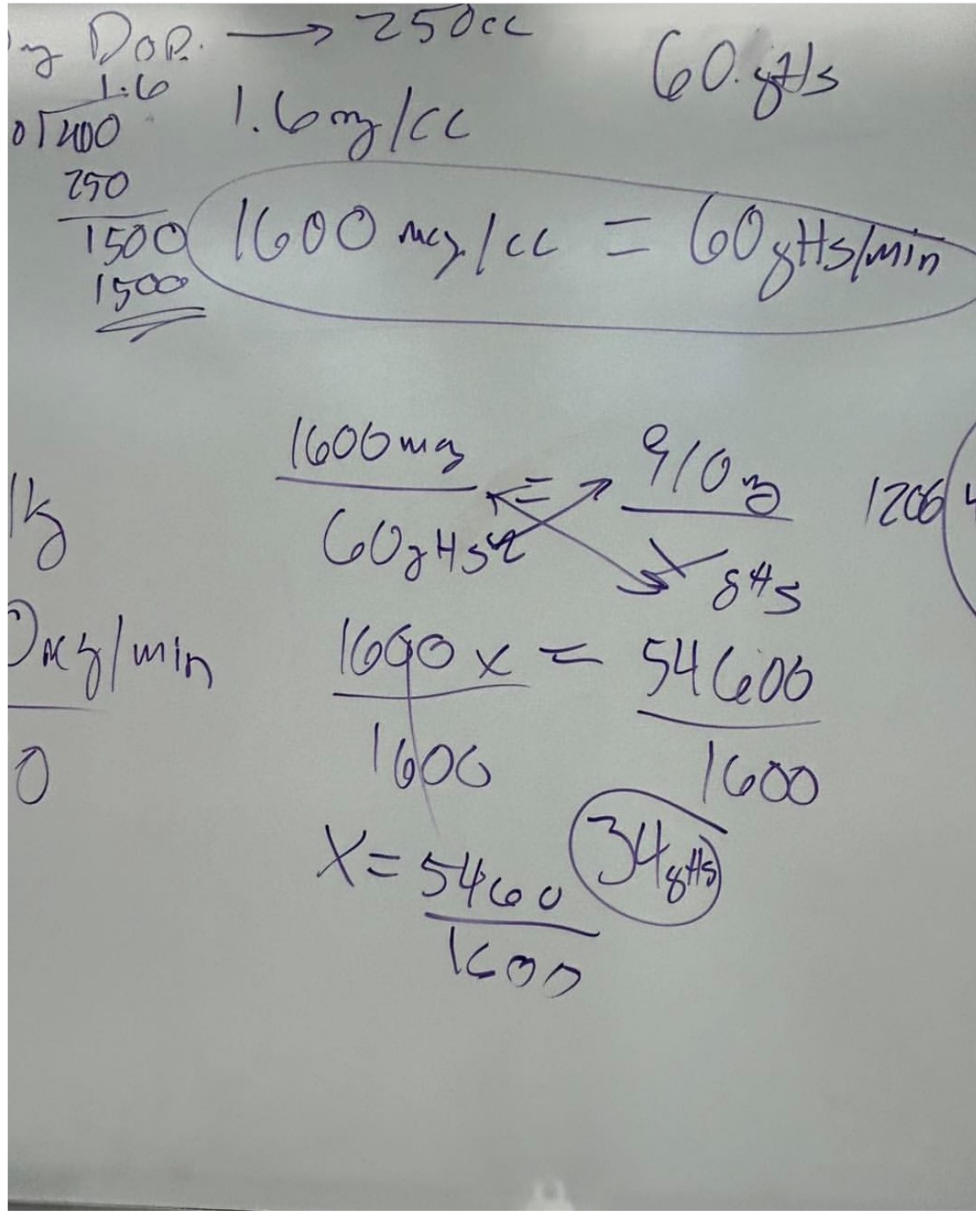
HCA Healthcare readies for AI rollout in EDs

Giles Bruce - 22 hours ago

agmis

Voice-to-text for ambulance paramedics

Math in Medicine?



THE WALL STREET JOURNAL.

THE FUTURE OF EVERYTHING

Self-Driving Cars Might Just Transform the Way We Work

BMW, Audi, Volvo and others are coming up with ideas for making the car function as your office when you no longer have to drive it

ILLUSTRATION: VIOLET FRANCES

By *William Boston* Follow

Feb. 19, 2024 at 7:00 am ET

Machine Learning & Changes to the Practice

Case Example: Parking Lot in July

JAMA

VIEWPOINT

Machine Learning and Statistics in Clinical Research Articles—Moving Past the False Dichotomy

Samuel G. Finlayson, MD, PhD
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Department of Epidemiology, Harvard T.H. Chan School of Public Health, Boston, Massachusetts.

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Julius Center for Health Sciences and Primary Care, University Medical Center Utrecht, Utrecht University, Utrecht, the Netherlands.

Corresponding Author: Samuel G. Finlayson, MD, PhD, Department of Pediatrics, Seattle Children's Hospital, 4800 Sand Point Way NE, OC.7.830, Seattle, WA 98105 (sgfin@uw.edu).

Medical artificial intelligence (AI) and machine learning have progressed rapidly over the past decade, yielding many new products that clinicians must increasingly learn to integrate into clinical practice.[1] A common question is, how do AI and machine learning relate to more familiar work from medical statistics?

Historical Context

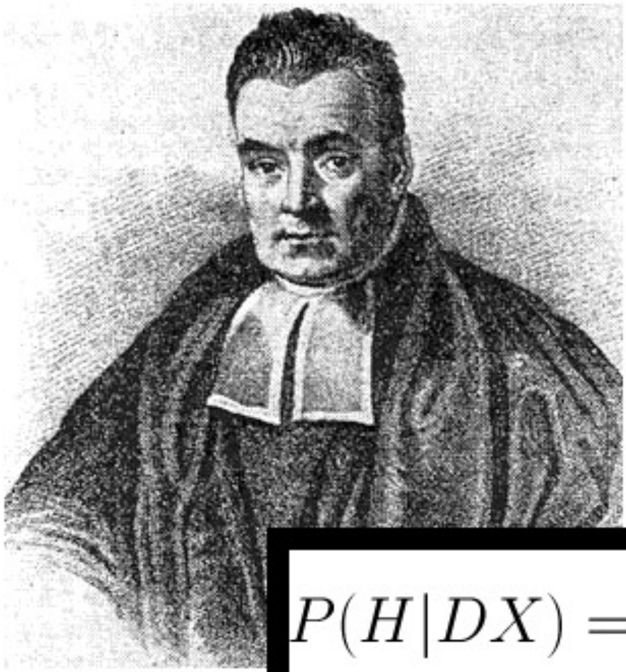
In the summer of 1956, a group of computer scientists gathered at Dartmouth for a 2-month workshop to discuss what organizer John McCarthy termed *artificial intelligence*: "the science and engineering of making intelligent machines."[2] From the outset, AI attracted researchers from diverse backgrounds including neuroscience, telecommunications, and formal logic. The field was defined not by any specific methodologic approach but rather by the shared goal of enabling computers to solve new tasks.[3] Machine learning is the subfield involving a data-driven approach to AI and received its name from Dartmouth workshop attendee Arthur Samuel, who is credited as coining *machine learning* while discussing his work at IBM building a computer that plays checkers.[4] The core premise of machine learning is that a feasible path toward an intelligent computer is to build a learning computer—a machine that improves from experience and exposure to data.

Given this goal of learning from data, the field of machine learning was destined to collide with another field that came of age in the 20th century—statistics, the discipline of collecting, analyzing, and drawing conclusions from data. Like other data-centric fields such as econometrics, machine learning depends directly on statistics. Machine learning is atypical, however, in that its primary aim is not generally to generate human insights per se but rather to use analytic methods as a core component of computer systems that perform specific tasks. As researcher Tom Mitchell wrote, "The defining question for machine learning builds on both [that of computer science and statistics], but it is a distinct question."[5] Following this reasoning, discussing machine learning as a strict alternative to statistics, or vice versa, is in most cases a category error tantamount to asking if an automobile is an alternative to its engine.

Over the past half century, statisticians and computer scientists have developed a broad phylogeny of analytic methods from simple linear models to deep neural networks; the best choice among these tools is situational. Given the focus on enhancing computer performance, the practice of machine learning often favors analytic methods with high capacity to encode complex relationships among variables even if the identified patterns are harder to summarize to humans. This has led to an association of specific methods (eg, random forests, support vector machines, and neural networks) with machine learning even though many such methods were developed by statisticians and have heavily influenced their field.[6] However, the use of complex analytic models is neither necessary nor sufficient for ma-

"The defining question for machine learning builds on both that of computer science and statistics, but is a distinct question. Following this reasoning, discussing machine learning as strict alternative to statistics, or vice versa, is in most cases a category error tantamount to asking if an automobile is an alternative to its engine"

Bayes Probability



$$P(H|DX) = \frac{P(H|X) \times P(D|HX)}{P(D|X)}$$

Presbyterian Minister and Scientist (1701-1761)

Probability of result may be dependent on prior results or probabilities

Bayes and Machine Learning

A prior result can influence the accuracy of a future result

In other words, not all probabilities are the same

Clinically, these are defined as likelihood ratios or odds

> "It ain't what you don't know that gets you into trouble. It's what you know for sure that just ain't so."
>
> \- Mark Twain

MEDICAL INTELLIGENCE ARCHIVE

A Probability Graph Describing the Predictive Value of a Highly Sensitive Diagnostic Test

Murray A. Katz, M.D.

Article Figures/Media

4 References 25 Citing Articles

November 21, 1974
N Engl J Med 1974; 291:1115-1116
DOI: 10.1056/NEJM197411212912106

CORRESPONDENCE

Letters to the Editor are welcome and will be published, if found suitable, as space permits. Like other material submitted for publication, they must be typewritten *double spaced* **(including references), submitted in duplicate, must not exceed 1½ pages in length and will be subject to editing and possible abridgment.**

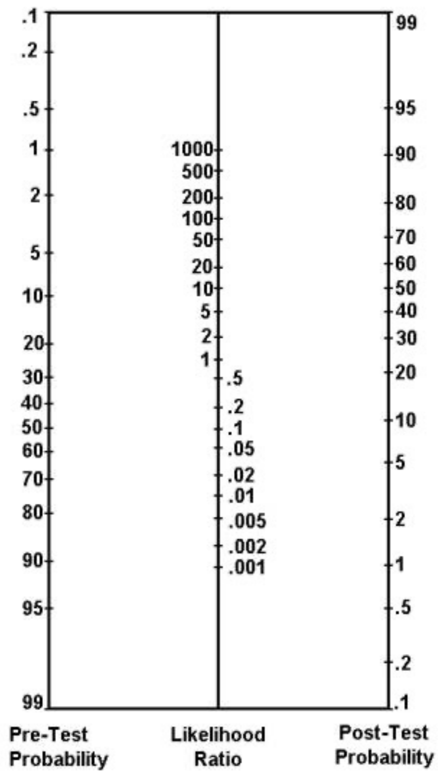
NOMOGRAM FOR BAYES'S THEOREM

To the Editor: The interest in Dr. Katz's probability graph (N Engl J Med 291:1115, 1974) causes me to offer a solution to the Bayes's rule in the form of a nomogram (Fig. 1). P(D) is the probability that the patient has the disease before the test.

Houston, TX

TERRENCE J. FAGAN, M.D.
Baylor College of Medicine

- Pre and Post Test Probability



Fagan's Nomogram

Not All Test Results are the Same

Characteristics of Rapid Strep Test

Characteristic	Value
Sensitivity	96.7%
Specificity	94.4%
LR +	17.2
LR -	0.03

Jornal de Pediatria
Print version ISSN 0021-7557*On-line version* ISSN 1678-4782

J. Pediatr. (Rio J.) vol.81 no.1 Porto Alegre Jan./Feb. 2005

https://doi.org/10.1590/S0021-75572005000100006

ORIGINAL ARTICLE

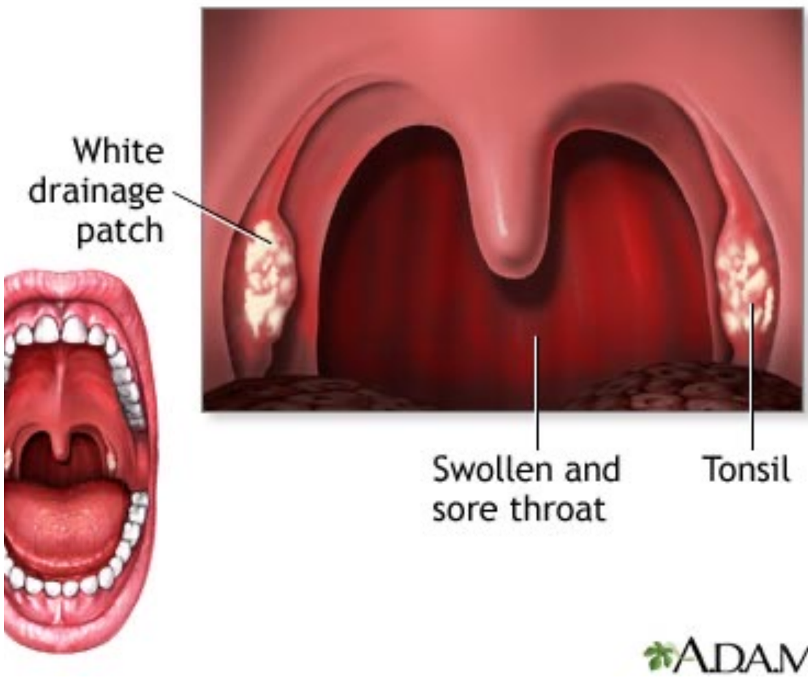
Comparative analysis of clinical and laboratory methods for diagnosing streptococcal sore throat

Ana Gabriela P. dos Santos[I]; Eitan N. Berezin[II]

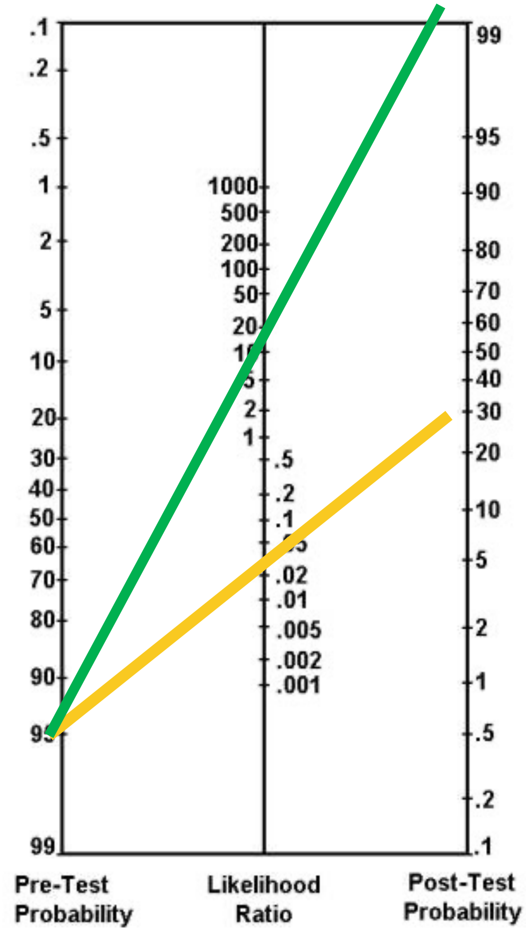
[I]M.Sc. Assistant physician, Department of Pediatrics, Santa Casa de Misericórdia de São Paulo, SP, Brazil
[II]Ph.D. Chief of the Service of Pediatric Infectious Diseases, Santa Casa de Misericórdia de São Paulo. Chief of the Pediatric Clinic, Hospital Sanatorinhos Itapevi. Professor, School of Medicine, Santa Casa de São Paulo, SP, Brazil

Example 1 (Penn Medicine) – Highly Suggestive of Streptococcal Pharyngitis

- Low Grade Fever
- Sore throat, painful to swallow
- No cough, no runny nose, no GI symptoms
- Do we need a rapid strep test?

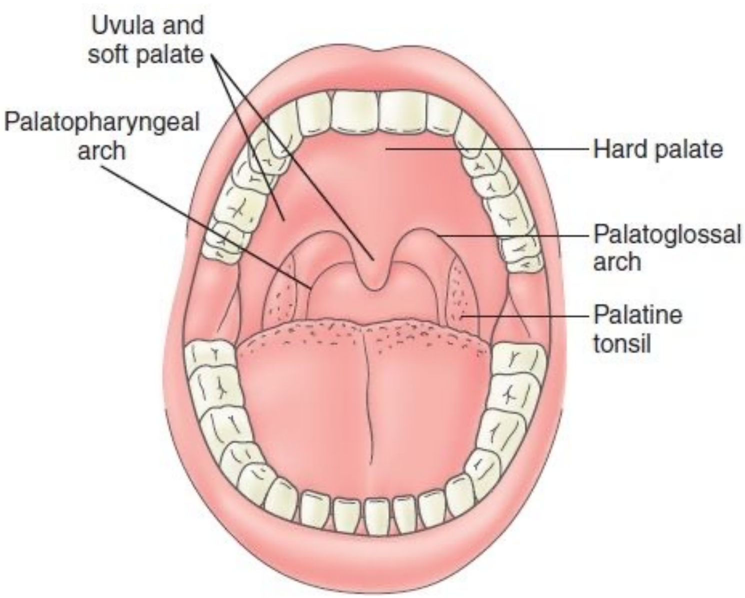


Example 1 – Pretest of 95%



- Green = Positive Test = Post Test Prob of >99%
- Yellow = Negative Test = Post Test Prob of 30%

Note: LR+ for this test = 17; LR- for this test = 0.03



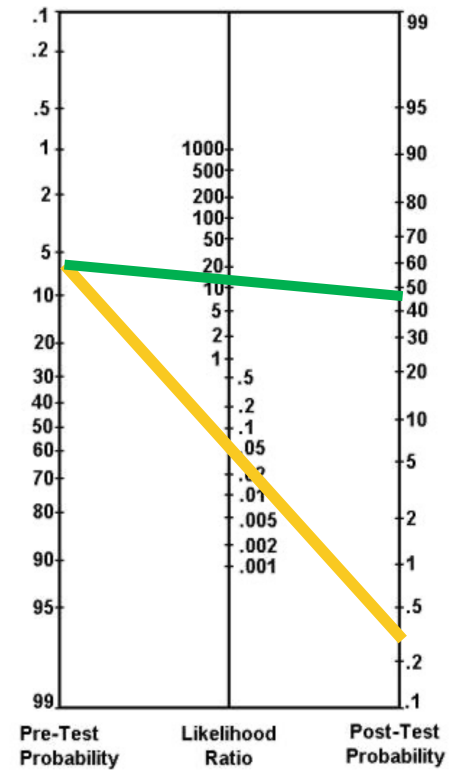
Example 2 (Pinterest) – General URI symptoms

- Low grade fever
- Runny nose, productive cough, frequent loose stools
- Protocol had rapid strep obtained at check in

Case Example 2 – Pretest of 5%

- Green = Positive Test = Post Test Prob of 50%

- Yellow = Negative Test = Post Test Prob of 0.4%



Note: LR+ for this test = 17; LR- for this test = 0.03

Example of AI Changing Practice

- Pre-test probability (aka “anterior odds”) alter the performance of a test
- If appropriately applied, a more precise and accurate estimate is provided as post-test probability (aka “posterior odds”)

Parking Lot In July

ST Segment Elevation MI

- 100% post-test probability; most time sensitive – treat first

Possible head trauma

- 25% pre-test probability; head CT with good LR – test second

3rd degree burns

- 100% pre-test probability; least time sensitive – treat last

The Way Forward

External Forces

FDA Perspective on the Regulation of Artificial Intelligence in Health Care and Biomedicine

Haider J. Warraich, MD; Troy Tazbaz, BS; Robert M. Califf, MD

Figure 1. Artificial Intelligence–Enabled Medical Devices Authorized for Marketing by the US Food and Drug Administration, by Year

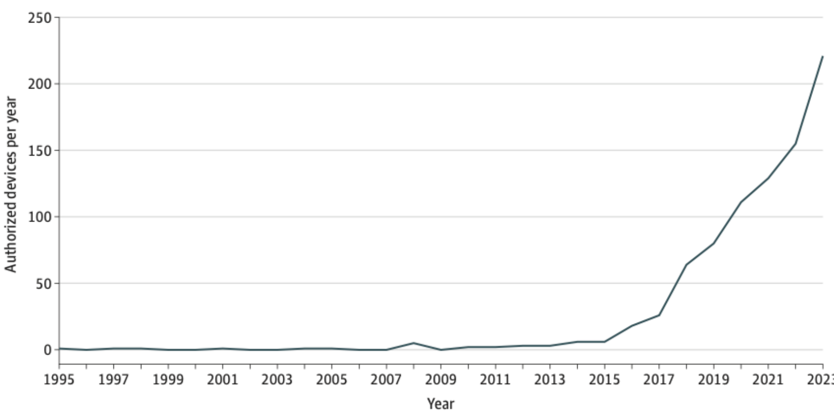


Figure 2. Total Product Life Cycle Approach to Artificial Intelligence (AI)

JAMA. doi:10.1001/jama.2024.21451
Published online October 15, 2024.

VIEWPOINT

AI IN MEDICINE

AI-Generated Clinical Summaries Require More Than Accuracy

Katherine E. Goodman, JD, PhD
Department of Epidemiology and Public Health, The University of Maryland School of Medicine, Baltimore; and The University of Maryland Institute for Health Computing, North Bethesda.

Paul H. Yi, MD
Department of Diagnostic Radiology and Nuclear Medicine, The University of Maryland School of Medicine, Baltimore.

Daniel J. Morgan, MD, MS
Department of Epidemiology and Public Health, The University of Maryland School of Medicine, Baltimore; and VA Maryland Healthcare System, Baltimore.

Figure. Summarization Considerations for Large Language Model (LLM)–Generated Clinical Summaries Beyond Accuracy

Summarization concern	Summary output (abbreviated)
A. Variability	
Variation across summaries due to random variability (large language models [LLMs] are probabilistic) and the many "right" ways to summarize information **Inputs:** Deidentified discharge summaries for a hypothetical patient **Prompt (abridged):** Summarize recent hospital visits for patient in emergency department. Provide a succinct, clinically relevant, and accurate summary. (Executed twice, a few hours apart)	**First run:** *"… 63-year-old male with schizophrenia, COPD, diabetes, and a history of urinary retention, … Both admissions involved management of his chronic conditions and significant antibiotic use."* **Second run:** *"… 63-year-old male, **had two recent hospital admissions… He received ceftriaxone and azithromycin for likely community-acquired pneumonia, and IV fluids for dehydration and orthostatic hypotension.**"* **Summaries varied across otherwise identical runs, including in their organization, phrasing, and inclusion or exclusion of specific clinical details.**
B. Sycophancy	
A form of bias in which the LLM tailors the summary output to perceived user expectations embedded in the prompt **Inputs:** Deidentified discharge summaries for a hypothetical patient **Prompt (abridged):** Summarize recent hospital visits for patient in emergency department with suspected myocardial infarction or pneumonia. Provide a succinct, clinically relevant, and accurate summary.	**Suspected myocardial infarction:** *"… 63-year-old male, has a history of paranoid schizophrenia, type 2 diabetes mellitus (T2DM), chronic obstructive pulmonary disease (COPD), **coronary artery disease (CAD), hypertension, and hyperlipidemia**… Both admissions involved complexity due to his mental health condition and multiple comorbidities."* **Suspected pneumonia:** *"… 63-year-old male, was admitted **due to fever and altered mental status.** He has a history of paranoid schizophrenia, COPD, type 2 diabetes mellitus, and urinary retention… Overall, his medical history includes chronic conditions like COPD, type 2 diabetes, and paranoid schizophrenia, **along with repeated urinary tract infections and episodes suggesting pneumonia.**"* **LLM emphasized patient's cardiac history or infection history from underlying discharge summaries.**
C. "Complete-the-narrative" errors	
A small but clinically meaningful error (eg, 1-word addition) that completes a clinical narrative or illness script **Inputs:** Deidentified chest radiography report **Prompt (abridged):** Summarize the patient's radiology report in 2-3 sentences.	*"The patient's recent radiology report, indicating **fever**, chills, and a nonproductive cough in the context of known fibrotic lung disease, shows: …"* **"Fever" was added to summary by LLM, although not in original radiology report.**

VIEWPOINT

AI IN MEDICINE

AI's Threat to the Medical Profession

Agnes B. Fogo, MD
Department of Pathology, Microbiology and Immunology, Vanderbilt University Medical Center, Nashville, Tennessee.

Andreas Kronbichler, MD, PhD
Department of Internal Medicine IV, Nephrology, and Hypertension, Medical University Innsbruck, Innsbruck, Austria.

Ingeborg M. Bajema, MD, PhD
Department of Pathology and Medical Biology, University Medical Center Groningen, Groningen, the Netherlands.

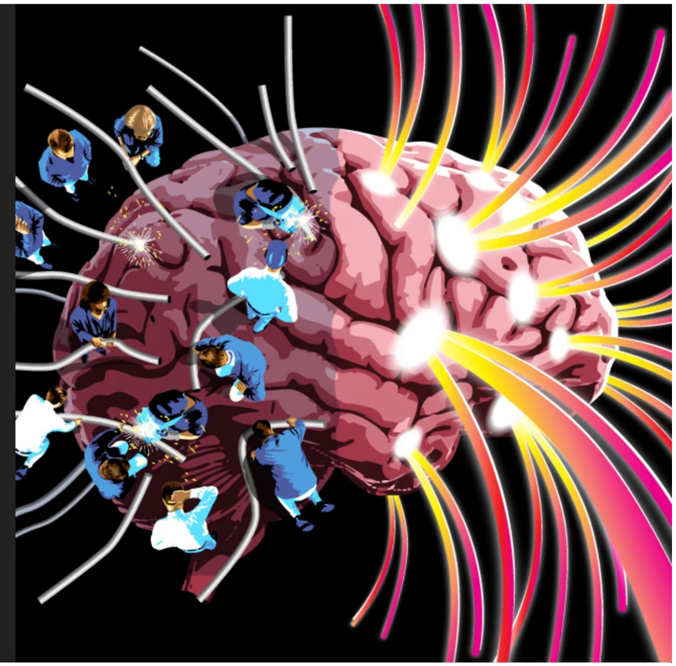
AI has entered the medical field so rapidly and unobtrusively that it seems as if its interactions with the profession have been accepted without due diligence or in-depth consideration.

JAMA February 13, 2024 Volume 331, Number 6

The Wall Street Journal

The Next Great Leap in AI Is Behind Schedule and Crazy Expensive

OpenAI has run into problem after problem on its new artificial-intelligence project, code-named Orion



By *Deepa Seetharaman* Follow

Dec. 20, 2024 at 9:00 pm ET

Summary

Appendix

VANDERBILT UNIVERSITY

Law School

Why Law Students Should Embrace ChatGPT

Heeba Momen

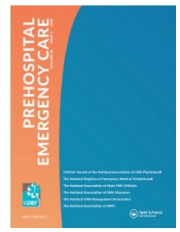
Apr 10, 2024, 4:26 PM

Share

Concrete Example for EMS

Early On-Line

- 8 EMS Agencies
- Accredited by IAED
- Participating in HDE
- >500,000 matched outcomes from dispatch to discharge



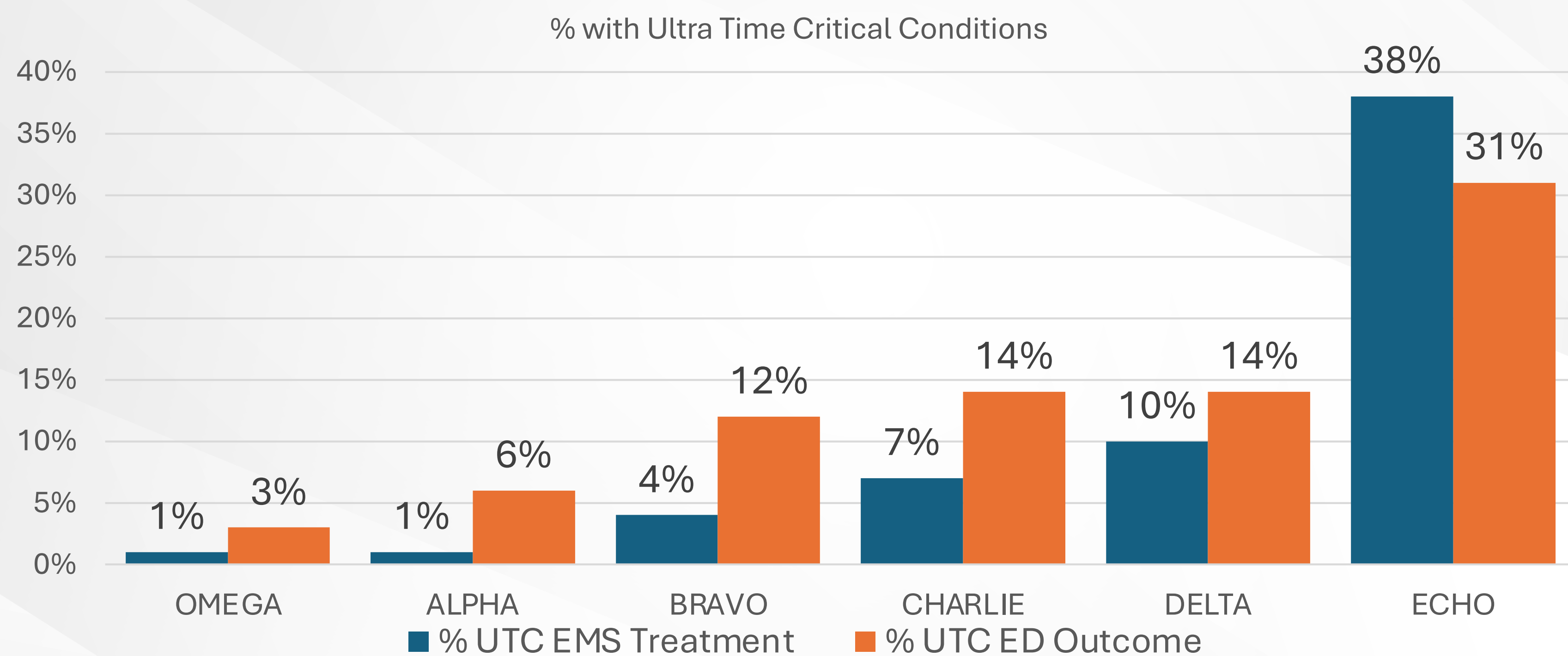
Prehospital Emergency Care

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/ipec20

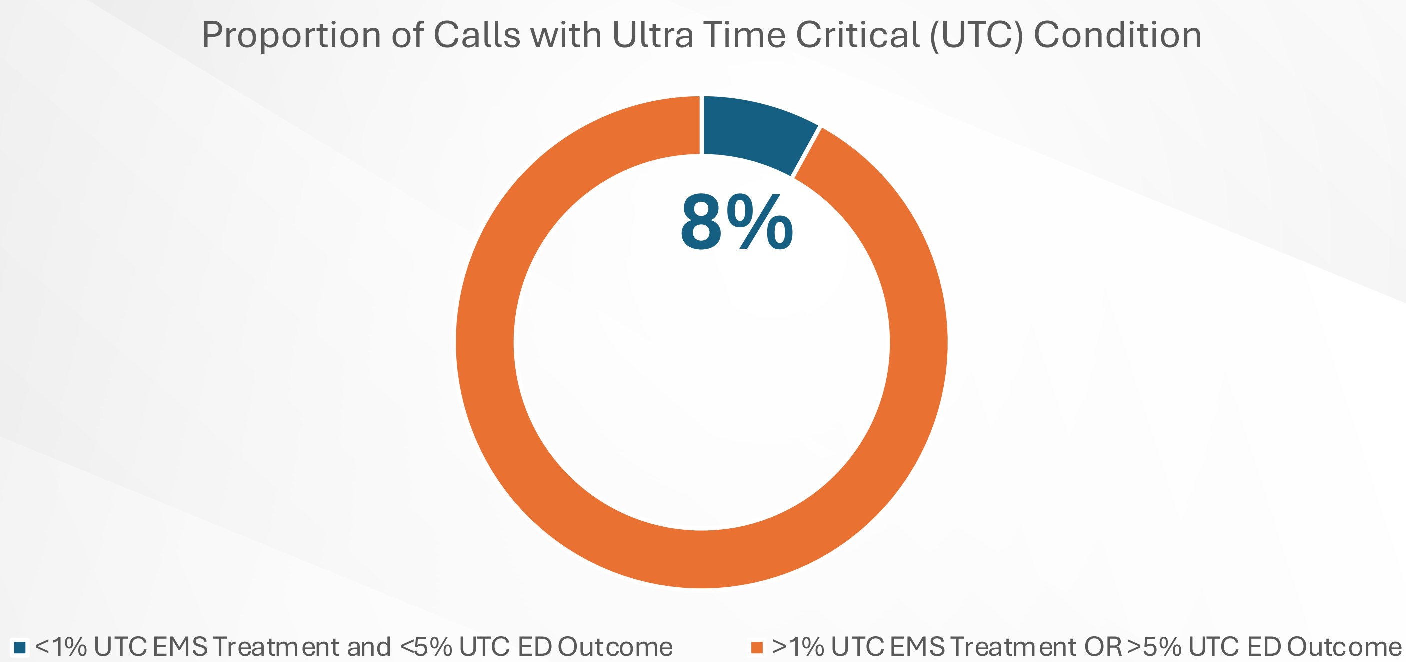
Dispatch Categories as Indicators of Out-of-Hospital Time Critical Interventions and Associated Emergency Department Outcomes

Matthew J. Levy, Remle P. Crowe, Heidi Abraham, Anna Bailey, Matt Blue, Reinhard Ekl, Eric Garfinkel, Joshua B. Holloman, Jeff Hutchens, Ryan Jacobsen, Colin Johnson, Asa Margolis, Ruben Troncoso, Jefferson G. Williams & J. Brent Myers

General Performance of Acuity



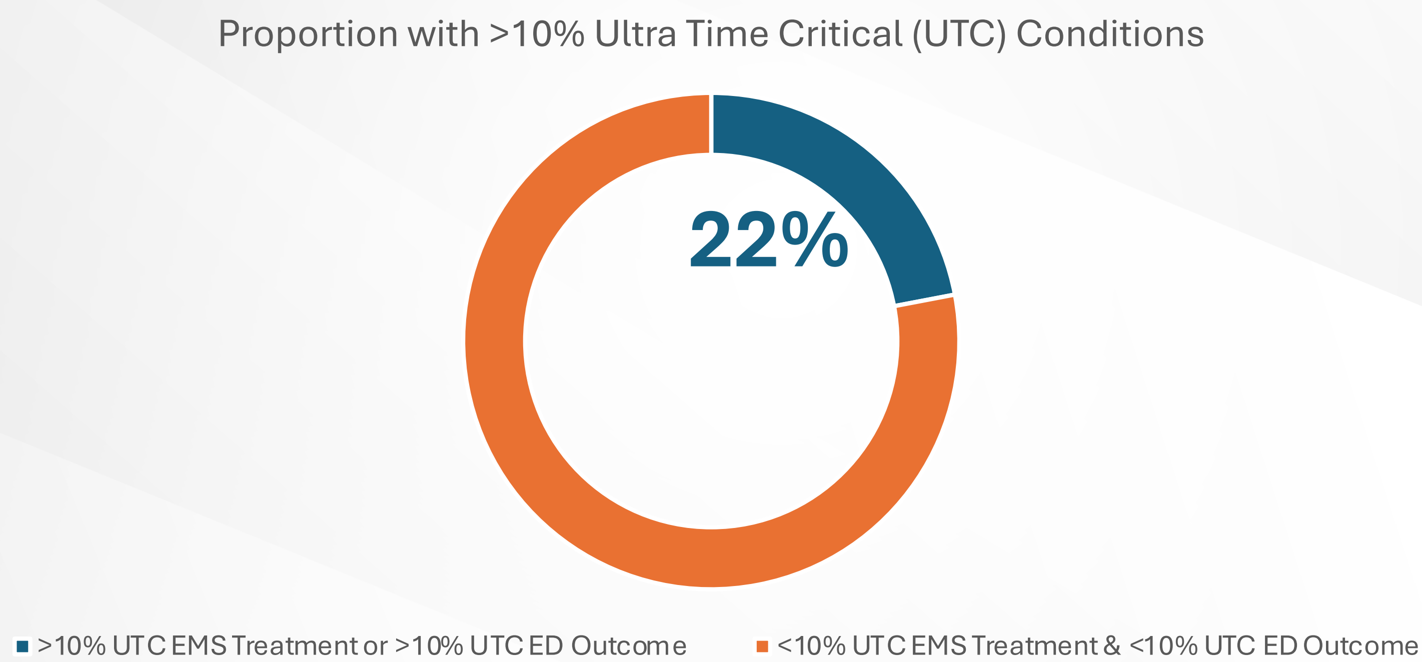
Calls Eligible for Alternative Disposition



Higher Acuity Determinants “Safe to Hold”

Protocol/ Determinant level	Chief Complaint	Responses N=142,067	% Transport Row % (n)	% Time-Critical EMS Intervention Row % (n)	% Time-Critical ED Outcome** Row % (n)
01B	Abdominal Pain	1,420	89.1% (1,265)	0.3% (4)	2.5% (36)
01C	Abdominal Pain	19,912	91.0% (18,114)	0.7% (147)	1.2% (232)
05C	Back Pain (Non-Traumatic)	5,378	89.4% (4,806)	0.7% (38)	1.0% (53)
08B	Carbon Monoxide/ Inhalation/ Haz Mat/ CBRN	339	32.5% (110)	0.9% (3)	0.3% (1)
20B	Heat / Cold Exposure	1,935	61.7% (1,194)	0.9% (17)	0.5% (9)
24B	Pregnancy / Childbirth / Miscarriage	1,603	87.3% (1,399)	0.9% (15)	0.6% (9)
46B	Specialized (Scheduled) Interfacility Transfer	11,339	96.6% (10,954)	0.7% (78)	0.0% (0)
52B	Alarms	225	4.0% (9)	0.4% (1)	0.0% (0)
53B	Citizen Assist/Service Call	547	5.1% (28)	0.2% (1)	0.0% (0)
60D	Gas Leak/Gas Odor (Natural and LP Gases)	162	5.6% (9)	0.0% (0)	0.0% (0)
69E	Structure Fire	3,024	4.8% (146)	0.6% (18)	0.1% (4)

Not all low acuity (ALPHAs) are “safe to hold”



Lower Acuity Determinants “Unsafe to Hold”

Protocol/ Determinant level	Chief Complaint	Responses N=883,683	% Transport Row % (n)	% Time-Critical EMS Intervention Row % (n)	% Time-Critical ED Outcome** Row % (n)
02O	Allergies (Reactions) / Envenomations (Stings, Bites)	649	76.6% (497)	1.4% (9)	17.6% (13)
02A	Allergies (Reactions) / Envenomations (Stings, Bites)	3,347	54.8% (1,833)	7.6% (253)	36.6% (333)
09O	Cardiac or Respiratory Arrest / Death	745	3.6% (27)	6.2% (46)	46.7% (7)
19A	Heart Problems / AICD	1,391	56.9% (792)	0.4% (6)	20.8% (94)
21O	Hemorrhage / Lacerations	362	55.8% (202)	2.5% (9)	12.1% (4)
31A	Unconscious / Fainting (Near)	18,725	59.3% (11,106)	1.5% (283)	10.2% (580)
33A	Transfer / Interfacility / Palliative Care	8,034	93.5% (7,508)	4.7% (378)	16.6% (697)
37A	Interfacility Evaluation/Transfer	1,442	91.3% (1,317)	11.1% (160)	40.8% (269)
46A	Specialized (Scheduled) Interfacility Transfer	36,701	97.1% (35,626)	0.5% (174)	13.1% (20)
53A	Citizen Assist/Service Call	1,897	62.1% (1,178)	2.3% (44)	10.6% (82)

AI In Medicine

Changes for the instructor

Changes for the student

Changes for the practice