

AI, ML, and Pediatric Sepsis

Tellen D. Bennett, MD, MS
Professor, Biomedical Informatics and Pediatrics
University of Colorado School of Medicine
PICU Attending Physician, Children's Hospital Colorado

tell.bennett@cuanschutz.edu



Department of Biomedical Informatics

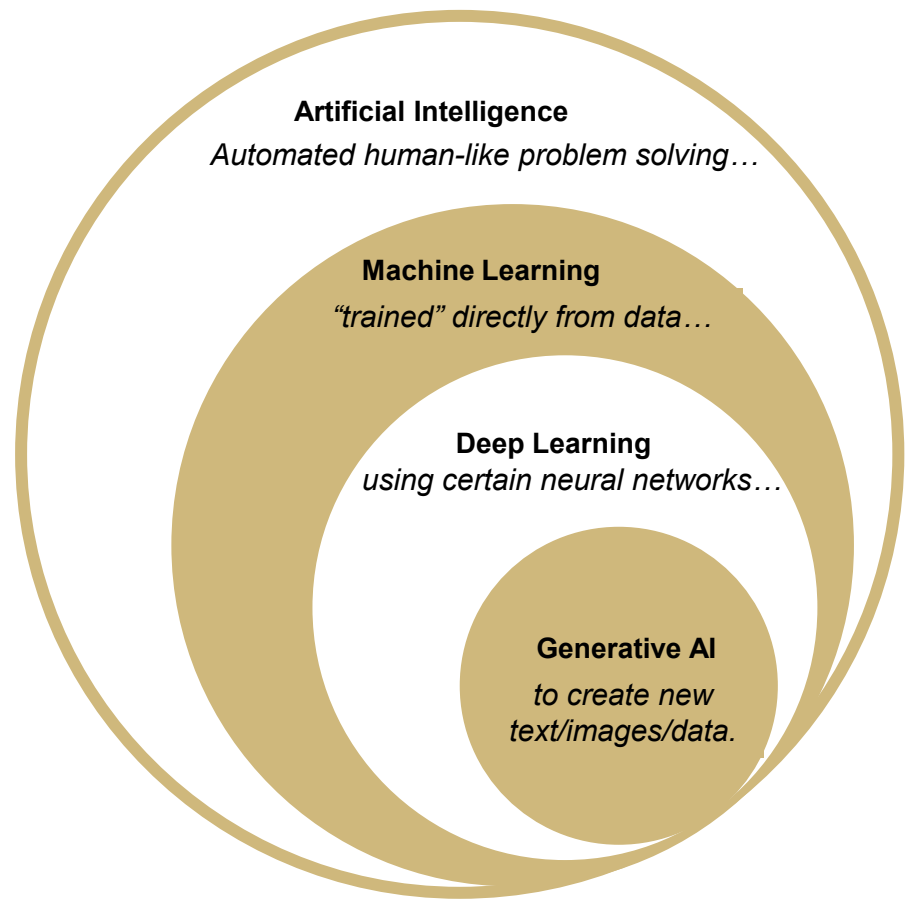
SCHOOL OF MEDICINE

UNIVERSITY OF COLORADO ANSCHUTZ MEDICAL CAMPUS

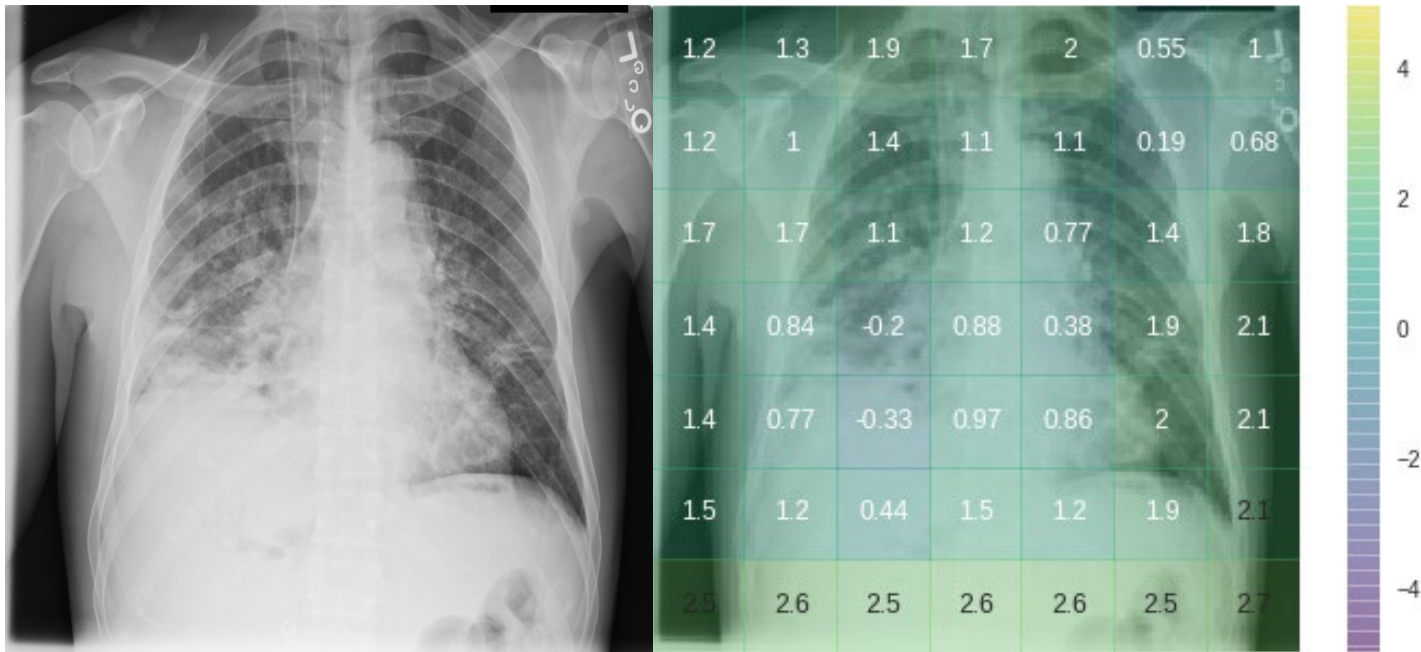


Children's Hospital Colorado

What is AI?



Sometimes, learning from data is not ideal

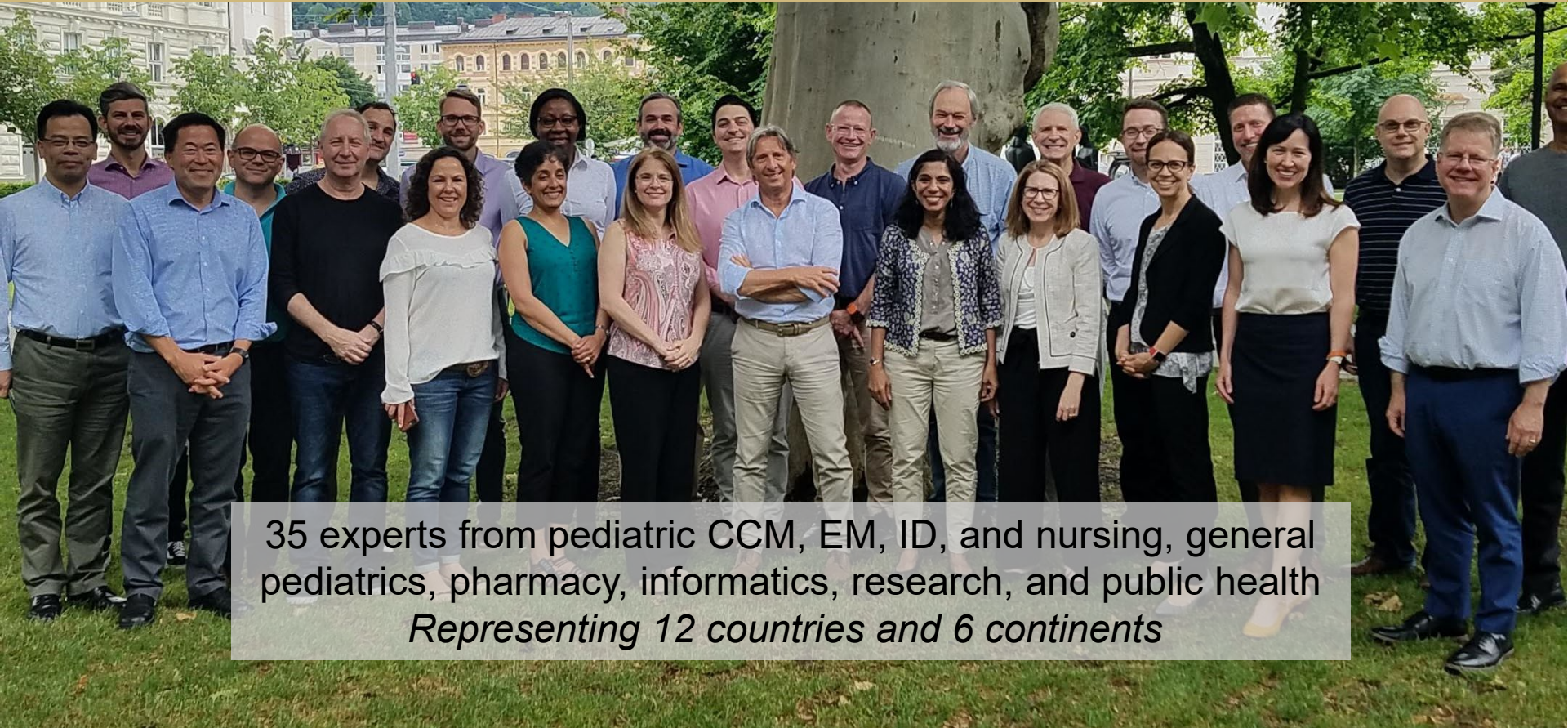


What are radiological deep learning models actually learning? John Zech (medium.com)

AI/ML: A Complete Story, Data to Patient Impact

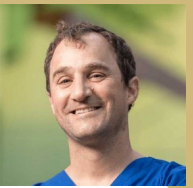


Pediatric Sepsis Definition Task Force, June 2019



35 experts from pediatric CCM, EM, ID, and nursing, general pediatrics, pharmacy, informatics, research, and public health
Representing 12 countries and 6 continents

Is this sepsis?



Fever



"Flu"



Sepsis



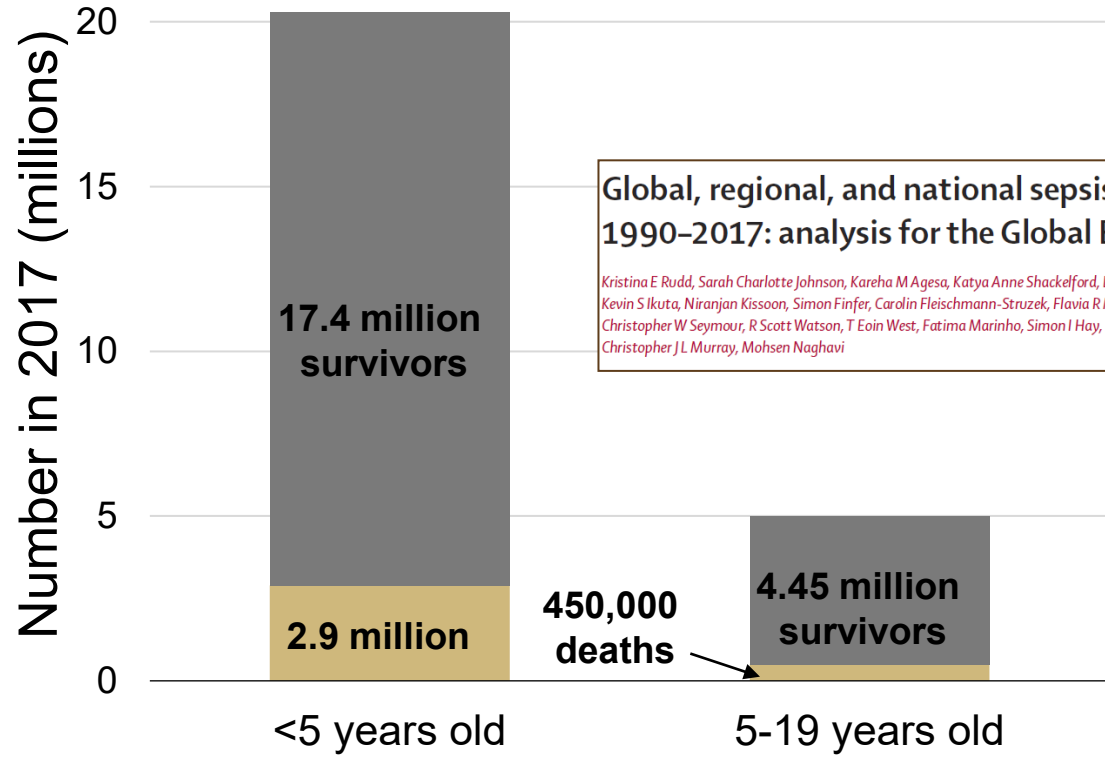
Septic shock

Sensitivity (early recognition)

Specificity (correct diagnosis)

Responsiveness to intervention

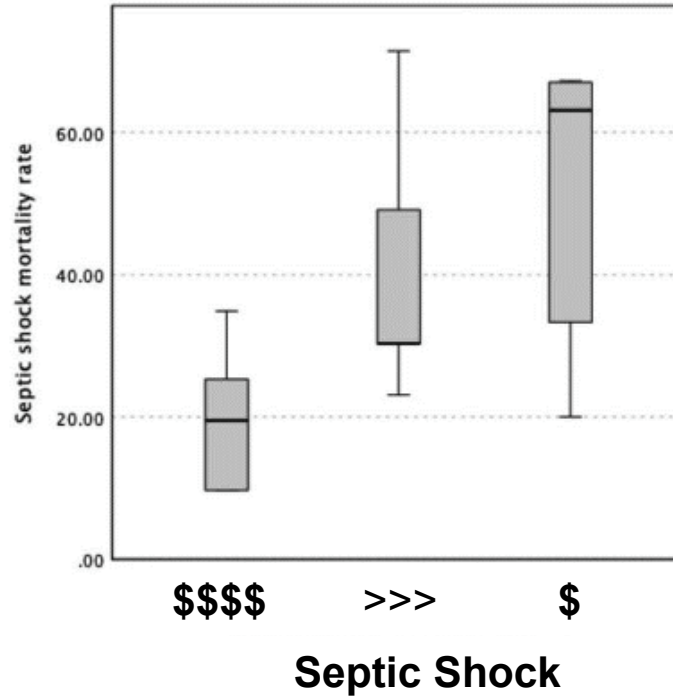
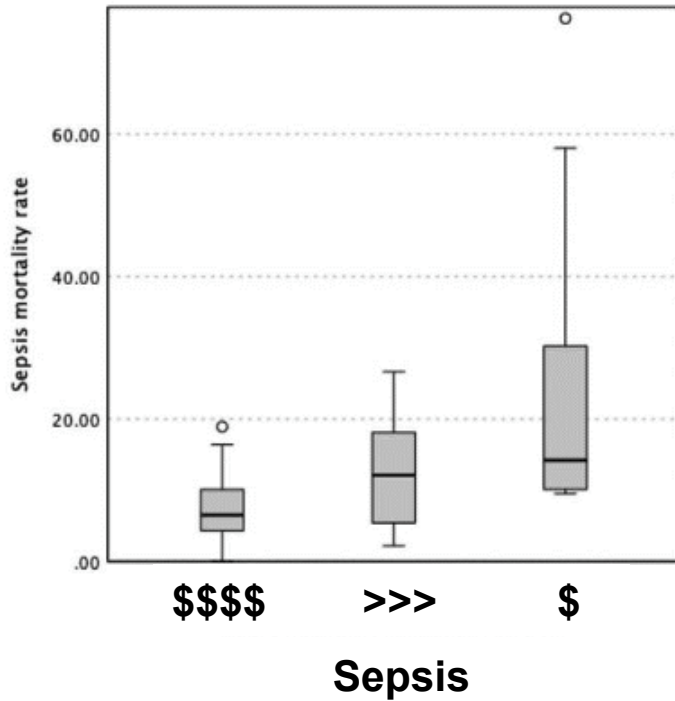
Pediatric Sepsis Burden



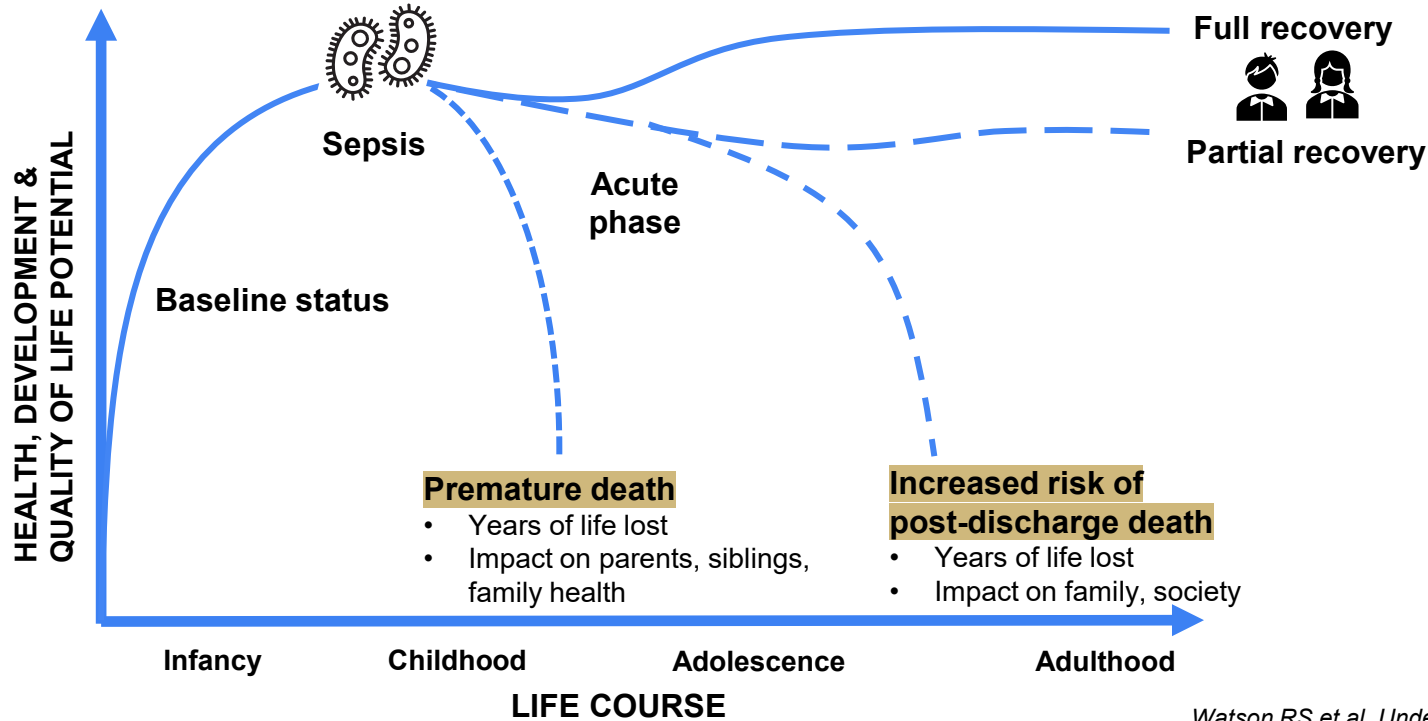
Global, regional, and national sepsis incidence and mortality, 1990–2017: analysis for the Global Burden of Disease Study

Kristina E Rudd, Sarah Charlotte Johnson, Kareha M Agesa, Katya Anne Shackelford, Derrick Tsoi, Daniel Rhodes Kievlan, Danny V Colombara, Kevin S Ikuta, Niranjan Kisson, Simon Finfer, Carolin Fleischmann-Struzek, Flavia R Machado, Konrad K Reinhart, Kathryn Rowan, Christopher W Seymour, R Scott Watson, T Eoin West, Fatima Marinho, Simon I Hay, Rafael Lozano, Alan D Lopez, Derek C Angus, Christopher J L Murray, Mohsen Naghavi

Mortality by World Bank Income Class



Long-term Impacts on Survivors

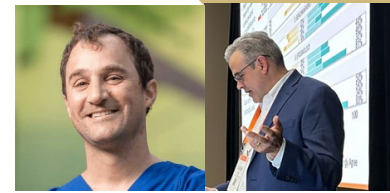


Watson RS et al, Under Review

Current Pediatric Criteria

International pediatric sepsis consensus conference:
Definitions for sepsis and organ dysfunction in pediatrics*

Brahm Goldstein, MD; Brett Giroir, MD; Adrienne Randolph, MD; and the Members of the International Consensus Conference on Pediatric Sepsis



- Not data-driven (“eminence-based”)
- Performed OK in some environments, poorly in others

By this definition, many patients in the ED or on the floor with non-life-threatening infection have “sepsis”

2016: New Adult Criteria

Special Communication | CARING FOR THE CRITICALLY ILL PATIENT

The Third International Consensus Definitions for Sepsis and Septic Shock (Sepsis-3)

Mervyn Singer, MD, FRCP; Clifford S. Deutschman, MD, MS; Christopher Warren Seymour, MD, MSc; Manu Shankar-Hari, MSc, MD, FFICM; Djillali Annane, MD, PhD; Michael Bauer, MD; Rinaldo Bellomo, MD; Gordon R. Bernard, MD; Jean-Daniel Chiche, MD, PhD; Craig M. Coopersmith, MD; Richard S. Hotchkiss, MD; Mitchell M. Levy, MD; John C. Marshall, MD; Greg S. Martin, MD, MSc; Steven M. Opal, MD; Gordon D. Rubenfeld, MD, MS; Tom van der Poll, MD, PhD; Jean-Louis Vincent, MD, PhD; Derek C. Angus, MD, MPH
JAMA. 2016;315(8):801-810. doi:10.1001/jama.2016.0287

Box 3. New Terms and Definitions

- Sepsis is defined as life-threatening organ dysfunction caused by a dysregulated host response to infection.

- ADULTS ONLY
- Data-driven + consensus
- High resource countries only

Pediatric Sepsis Definition Task Force Timeline



2018

- SCCM support
- Panel formation

2019

- Salzburg Kick-Off

2020/21

- Systematic review
- International survey
- Successful NIH funding (Bennett, Sanchez-Pinto)

2022

- Other Manuscripts
- Data Curation

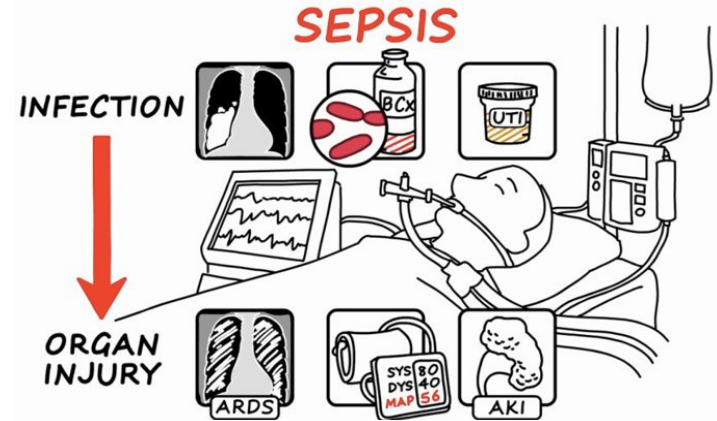
2023

- Analyses
- Delphi process
- Consensus

2024: Dissemination

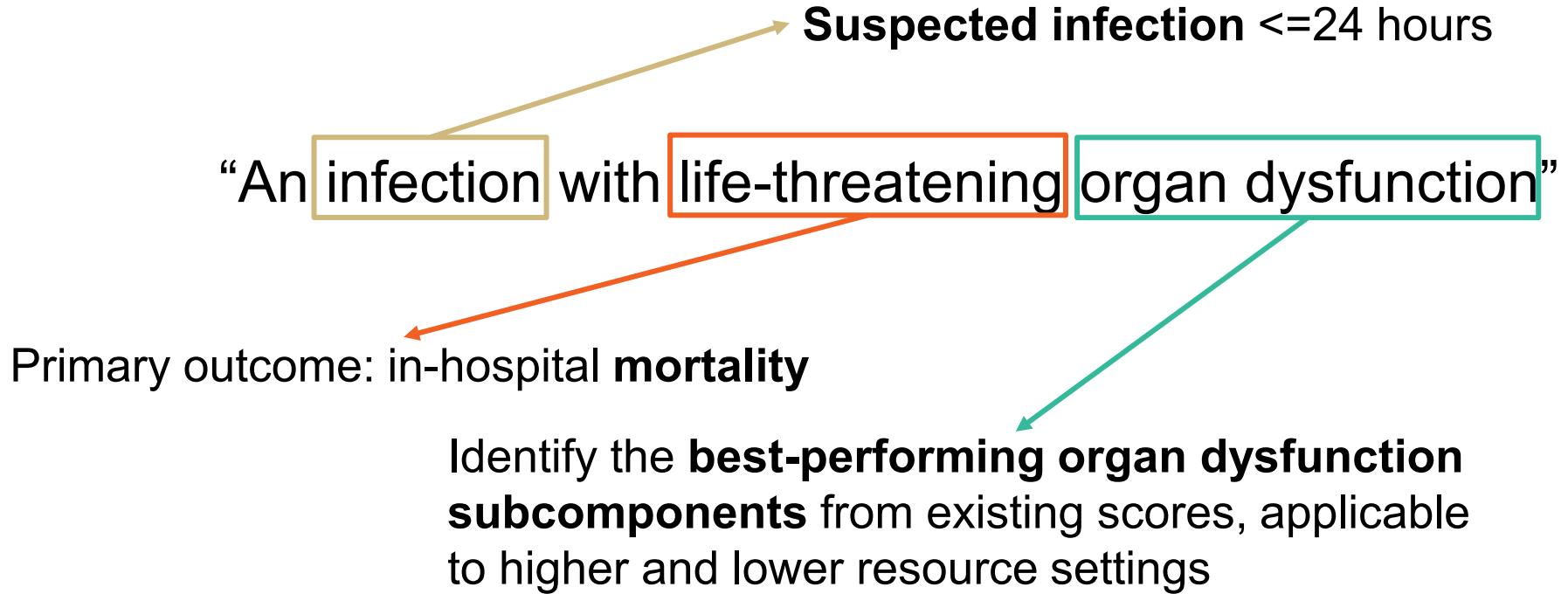
Conceptual Framework

Pediatric Sepsis =
“An infection with
life-threatening
organ dysfunction”

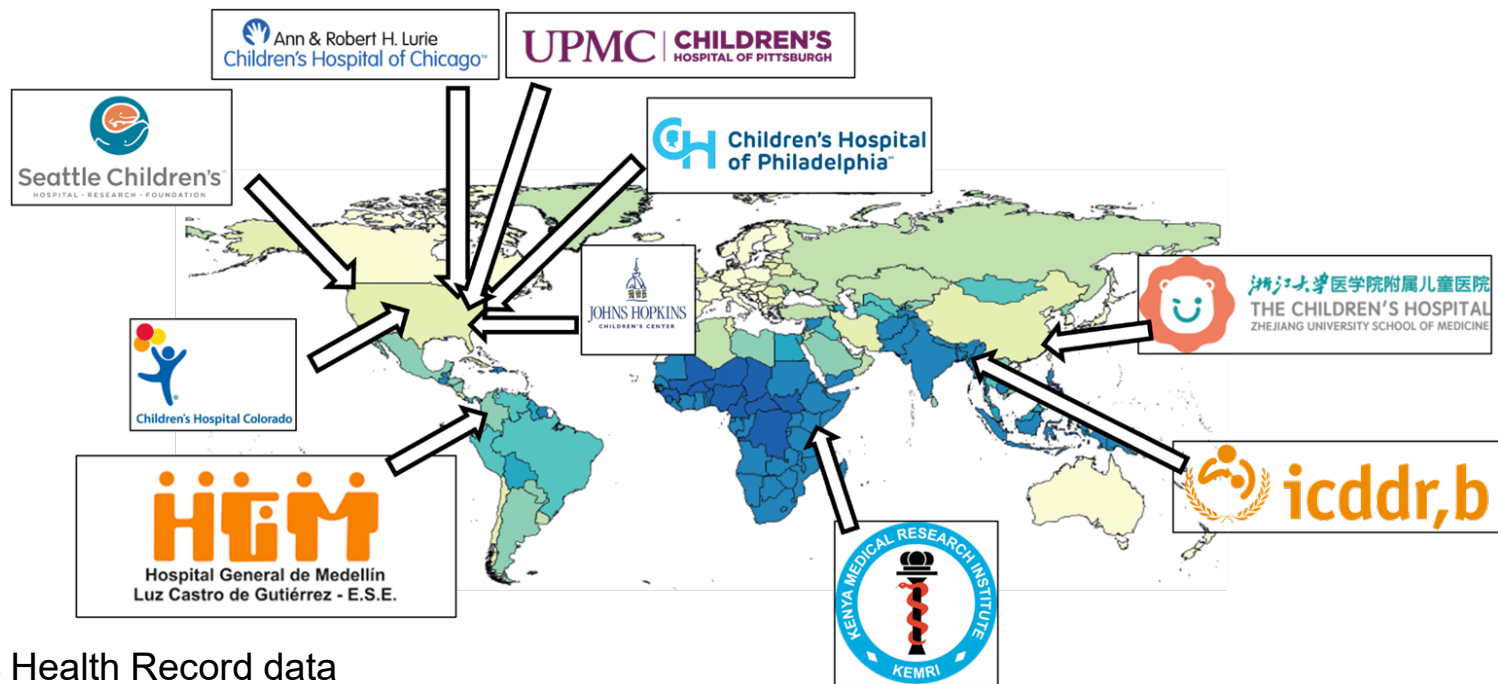


Source: JAMA Twitter feed, 2016

Conceptual Framework

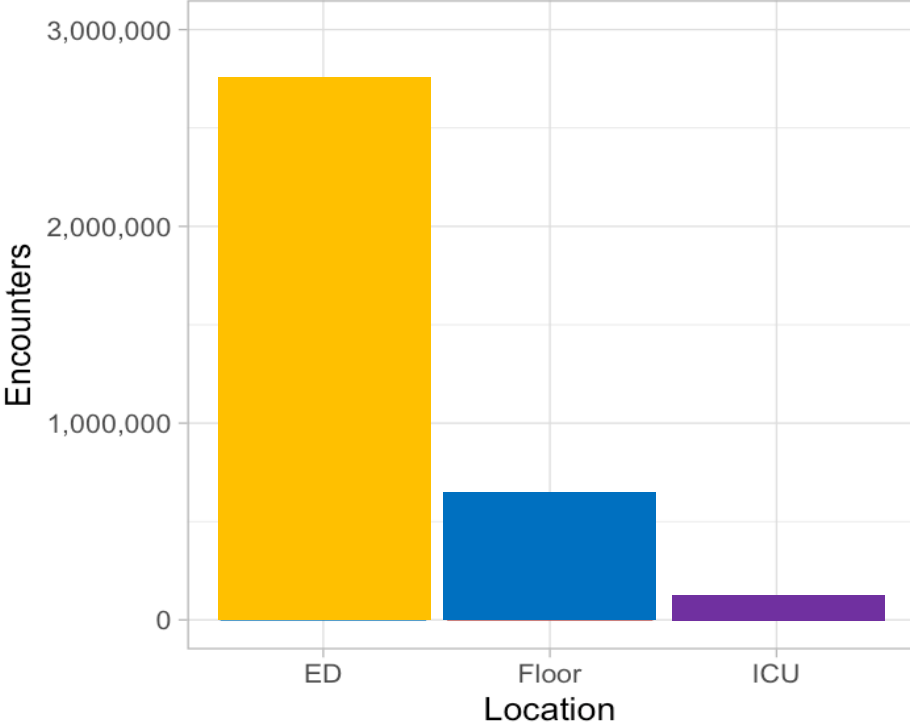


10 Study Sites: 6 Higher and 4 Lower Resource Settings

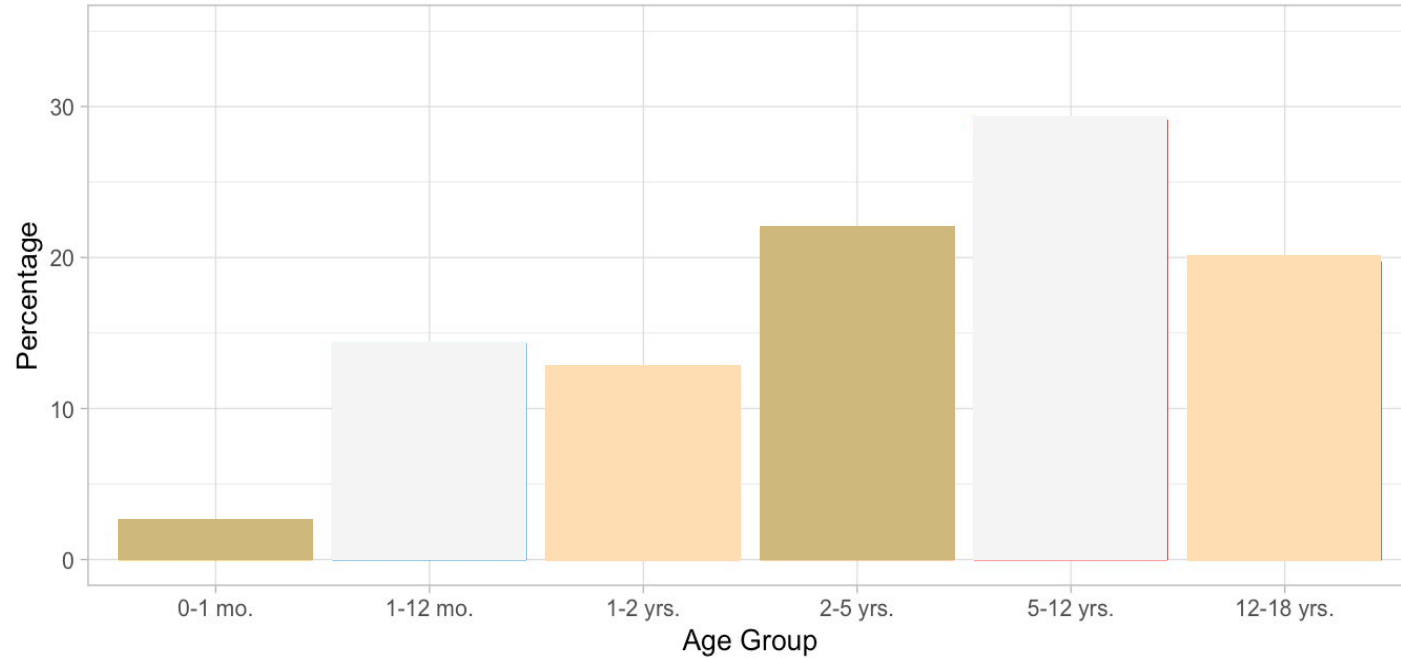


- Electronic Health Record data
- Date range 2010-2019

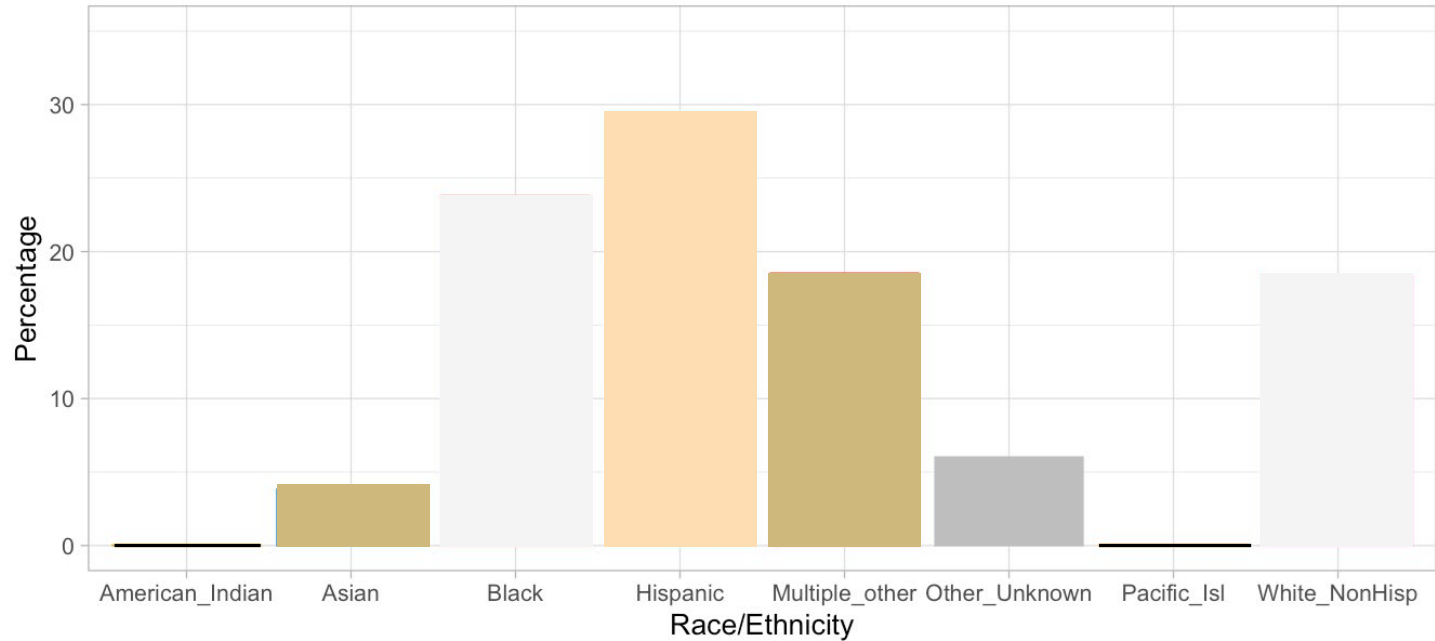
Cohort Size: >3.6 million Pediatric Hospital Encounters



Representative Population: Adequate Age Distribution

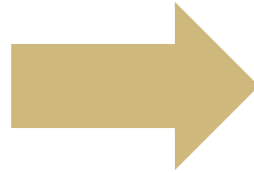
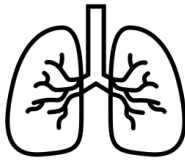


Representative Population: Diverse Race and Ethnicity



STEP 1 RESULTS:

Identify the best organ dysfunction subcomponents of existing scores



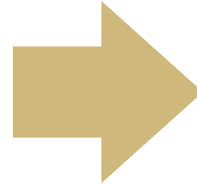
STEP 2 RESULTS: Sepsis Models Using Machine Learning

All-Stars



Machine Learning

$$\begin{pmatrix} 0 & 1 & 0 & \dots & 0 \\ 1 & 0 & 1 & \dots & 1 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 1 & 0 & \dots & 1 \end{pmatrix}$$



Model 1: Eight Organs

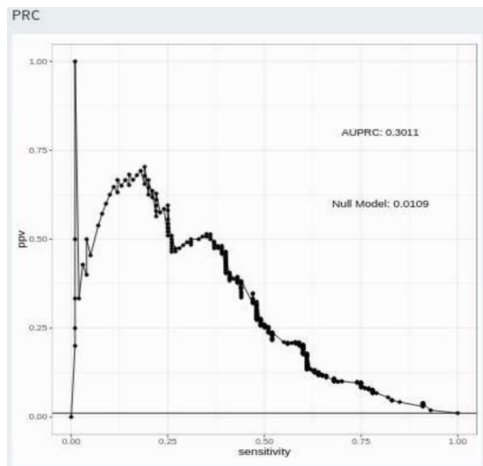
- Cardiovascular
- Respiratory
- Coagulation
- Neurologic
- Endocrine
- Renal
- Immuno
- Hepatic

Model 2: Four Organs

- Cardiovascular
- Respiratory
- Coagulation
- Neurologic

STEP 3 RESULTS:

Translate the Best Sepsis Model to the Phoenix Sepsis Score



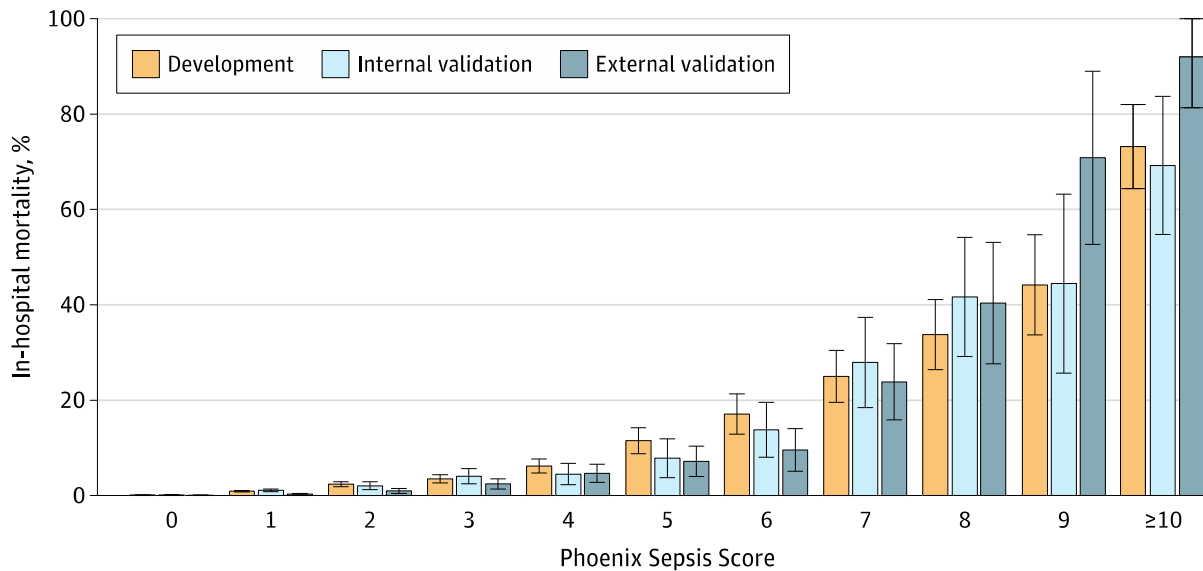
One integer, 0-13

$$\begin{pmatrix} 0 & 1 & 0 & \dots & 0 \\ 1 & 0 & 1 & \dots & 1 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 1 & 0 & \dots & 1 \end{pmatrix}$$

STEP 3 RESULTS:

Phoenix Sepsis Score has Good Calibration in Higher Resource Sites

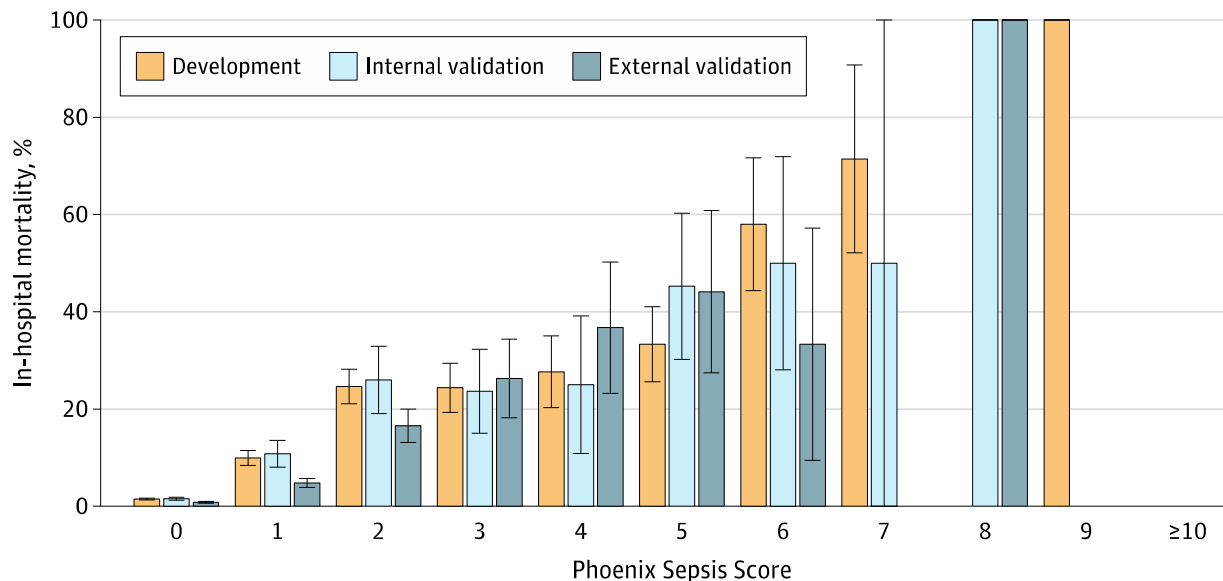
A In-hospital mortality



STEP 3 RESULTS:

Phoenix Sepsis Score has Good Calibration in Lower Resource Sites

A In-hospital mortality



STEP 4 RESULTS:

Translation of Phoenix Sepsis Score to Phoenix Sepsis/Septic Shock Criteria Selecting Thresholds

One integer, 0-13



Task Force Delphi process:

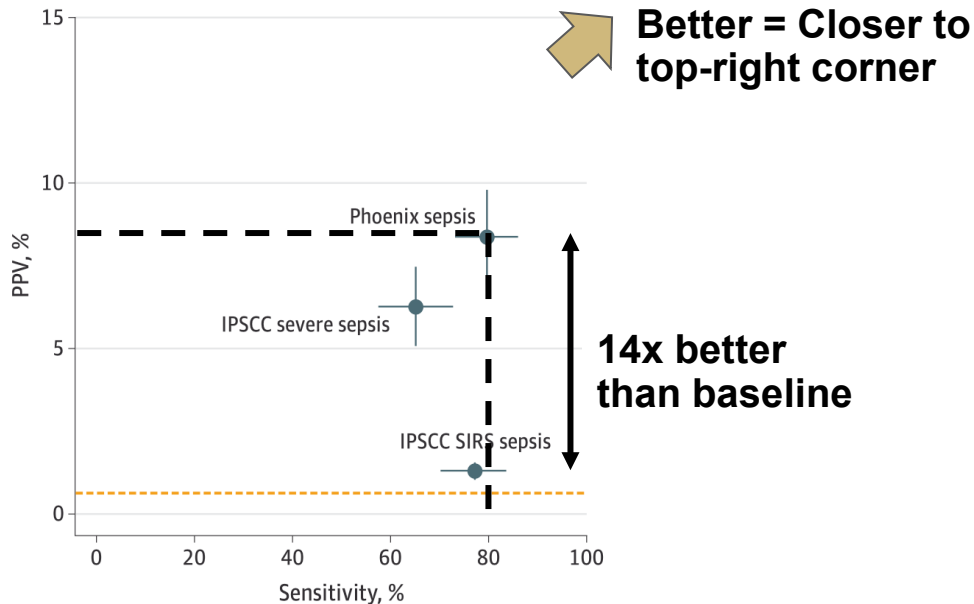
- **Sepsis**: ≥ 2 points on Phoenix Sepsis Score
- **Septic Shock**: Sepsis and ≥ 1 CV point

STEP 4 RESULTS:

PPV and Sensitivity for Phoenix Sepsis Criteria Higher than for 2005 IPSCC Sepsis Criteria

Interpretation recap

C PPV vs sensitivity for death at higher-resource sites 1-5 in children with no comorbidities (152 deaths among 24470 encounters)



Research

JAMA | **Original Investigation**

Development and Validation of the Phoenix Criteria for Pediatric Sepsis and Septic Shock

L. Nelson Sanchez-Pinto,* MD, MBI; Tellen D. Bennett,* MD, MS; Peter E. DeWitt, PhD; Seth Russell, MS; Margaret N. Rebull, MA; Blake Martin, MD; Samuel Akech, MBChB, MMED; David J. Albers, PhD; Elizabeth R. Alpern, MD, MSCE; Fran Balamuth, MD, PhD, MSCE; Melania Bembea, MD, MPH, PhD; Mohammad Jobayer Chisti, MBBS, MMed, PhD; Idris Evans, MD, MSc; Christopher M. Horvat, MD, MHA; Juan Camilo Jaramillo-Bustamante, MD; Niranjana Kissoon, MD; Kusum Menon, MD, MSc; Halden F. Scott, MD, MSCE; Scott L. Weiss, MD; Matthew O. Wiens, PharmD, PhD; Jerry J. Zimmerman, MD, PhD; Andrew C. Argent, MD, MBBCh, MMed; Lauren R. Sorce, PhD, RN, CPNP-AC/PC; Luregn J. Schlapbach, MD, PhD; R. Scott Watson, MD, MPH; and the Society of Critical Care Medicine Pediatric Sepsis Definition Task Force

* Co-first author

2024

Research

JAMA | **Original Investigation** | **CARING FOR THE CRITICALLY ILL PATIENT**

International Consensus Criteria for Pediatric Sepsis and Septic Shock

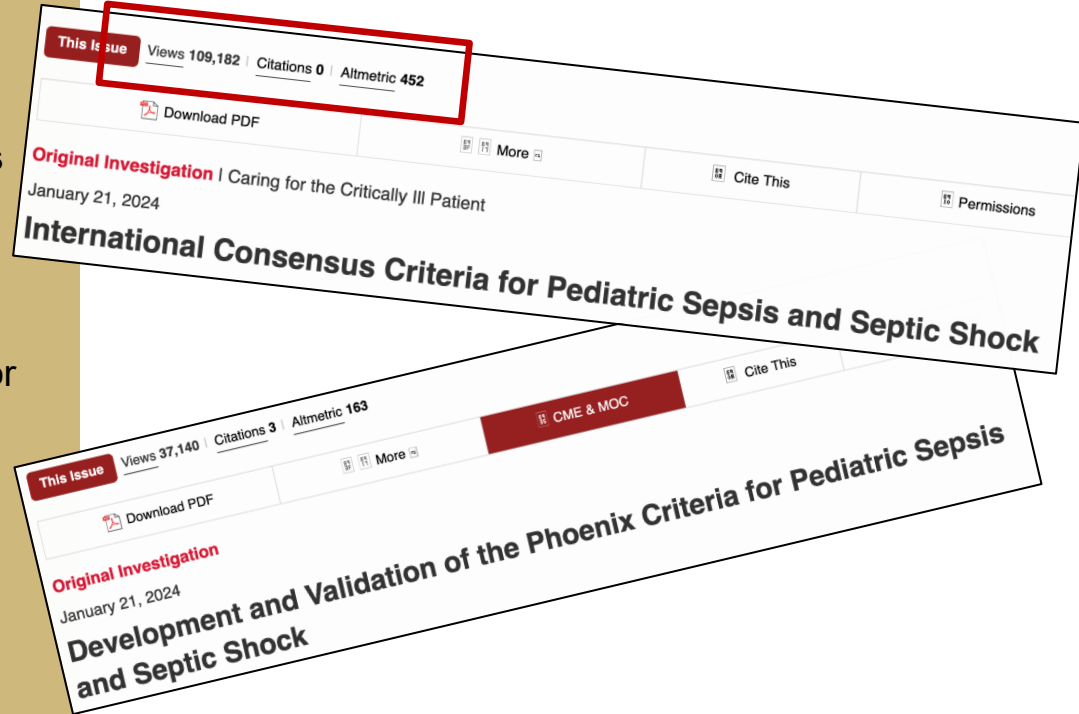
Luregn J. Schlapbach,* MD, PhD; R. Scott Watson,* MD, MPH; Lauren R. Sorce,* PhD, RN; Andrew C. Argent,* MD, MBBCh, MMed; Kusum Menon, MD, MSCE; Mark W. Hall, MD; Samuel Akech, MBChB, MMED, PhD; David J. Albers, PhD; Elizabeth R. Alpern, MD, MSCE; Fran Balamuth, MD, PhD, MSCE; Melania Bembea, MD, PhD; Paolo Biban, MD; Enitan D. Carrol, MBChB, MD; Kathleen Chiotos, MD; Mohammad Jobayer Chisti, MBBS, MMed, PhD; Peter E. DeWitt, PhD; Idris Evans, MD, MSc; Cláudio Flauzino de Oliveira, MD, PhD; Christopher M. Horvat, MD, MHA; David Inwald, MB, PhD; Paul Ishimine, MD; Juan Camilo Jaramillo-Bustamante, MD; Michael Levin, MD, PhD; Rakesh Lodha, MD; Blake Martin, MD; Simon Nadel, MBBS; Satoshi Nakagawa, MD; Mark J. Peters, PhD; Adrienne G. Randolph, MD, MS; Suchitra Ranjit, MD; Margaret N. Rebull, MA; Seth Russell, MS; Halden F. Scott, MD; Daniela Carla de Souza, MD, PhD; Pierre Tissieres, MD, DSc; Scott L. Weiss, MD, MSCE; Matthew O. Wiens, PharmD, PhD; James L. Wynn, MD; Niranjana Kissoon, MD; Jerry J. Zimmerman, MD, PhD; L. Nelson Sanchez-Pinto, MD; Tellen D. Bennett, MD, MS; and the Society of Critical Care Medicine Pediatric Sepsis Definition Task Force

* Co-first authors



IMPACT

- Overall goal: Decrease the number of sepsis deaths and improve long-term outcomes with more accurate diagnosis
- Deployment started in electronic health records across the country
- We have developed a mobile application for use in low resource environments
- In clinical use already – *I used the new criteria last week in the ICU*



Locally Made (NIH Funded)



Eunice Kennedy Shriver National Institute
of Child Health and Human Development

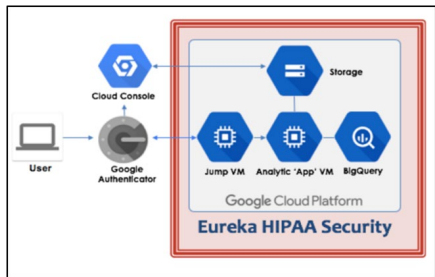
Site Data



Core Data Science Team



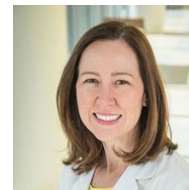
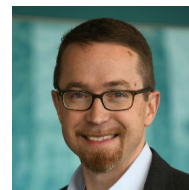
Computing Environment



Other CU Contributors



Task Force Members



Funding



Eunice Kennedy Shriver National Institute
of Child Health and Human Development

R01 HD105939



National Center
for Advancing
Translational Sciences



National Heart, Lung,
and Blood Institute

Extra Slides

What about ChatGPT etc. (Generative AI)?

First: What is a large language model (LLM)?

- A type of deep learning model (a transformer) trained to predict sequences
 - Text is sequences of words
- Trained on enormous amounts of text
 - (generally, available on the internet)
- General LLMs are very expensive to train (computing resources)
 - Although specific LLMs have been trained affordably

How was ChatGPT built?

Step 1

Collect demonstration data and train a supervised policy.

A prompt is sampled from our prompt dataset.

A labeler demonstrates the desired output behavior.

This data is used to fine-tune GPT-3.5 with supervised learning.



Step 2

Collect comparison data and train a reward model.

A prompt and several model outputs are sampled.

A labeler ranks the outputs from best to worst.

This data is used to train our reward model.



Step 3

Optimize a policy against the reward model using the PPO reinforcement learning algorithm.

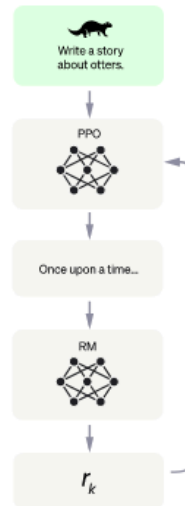
A new prompt is sampled from the dataset.

The PPO model is initialized from the supervised policy.

The policy generates an output.

The reward model calculates a reward for the output.

The reward is used to update the policy using PPO.



Reinforcement Learning with Human Feedback

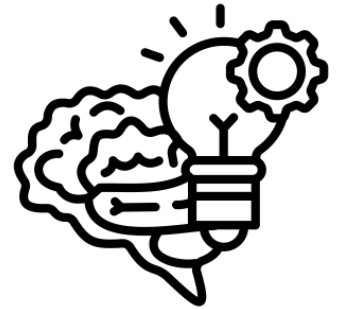
ChatGPT etc.

- **What will LLMs definitely be good for in medicine?**
 - Summarization
 - Documentation
 - Communications (including patient-facing chatbots)
 - Accelerating Analytics
 - Operations!



ChatGPT etc.

- **What might LLMs be good for in medicine?**
 - Diagnosis (first: adult, outpatient, conditions with a solid evidence base)
 - Interpretation of other complex data (waveforms, images, etc.) (long-term, massive compute needed)



LLMs: things to watch out for

- Hotel California for potentially sensitive data
- Has the model seen those data already (on medrxiv, pubmed, etc.)?
- "Hallucinations"
 - LLMs are like [insert very confident subspecialty]. They sound certain, even when they are wrong.



Specific Campus Expertise in LLMs

Yanjun Gao, PhD

Assistant Professor, DBMI

Start date Sept 1, 2024

