



2026 California Thoracic Society Annual Educational Conference & Chronic Obstructive Pulmonary Disease Symposium

Thursday March 12, 2026-Sunday March 15, 2026

Earn up to 19 CME/CEU/MOC Credits
Jointly Provided by AKH Inc., Advancing Knowledge in Healthcare
and the California Thoracic Society



PORTOLA HOTEL & SPA
AT MONTEREY BAY

Thursday March 12, 2026 (6 CME/CEU/MOC Credits)

COPD Symposium

Friday March 13, 2026 (6.5 CME/CEU/MOC Credits):

Advances in Interventional Pulmonary, Remote Monitoring in Pulmonary and Sleep Medicine,
Approach to Symptom Management in Chronic Lung Disease and Critical Care

Saturday March 14, 2026 (6.5 CME/CEU/MOC Credits)

Sepsis and Shock, Extracorporeal Membrane Oxygenation, Inpatient Pulmonary
Complications of Cancer Care

Sunday March 15, 2026

Fellow and Resident Track Symposium



Saturday March 14, 2026

Advances in Management of the Patient with Sepsis

8:00 am – 8:10 am: Welcome and Introduction

8:10 am – 8:55 am: Keynote Address – Phenotyping and Personalized Medicine in Sepsis

- **Angela Rogers, MD (Stanford)** - This speaker will discuss phenotyping in the patient with sepsis and septic shock and how close we are to precision medicine in managing sepsis.

8:55 am – 9:20 am: Incorporating Artificial Intelligence Decision Making in Identifying Sepsis

- **Gabriel Wardi, MD (UC San Diego)** - This speaker will describe how artificial intelligence can be used to identify the septic patient before they present with end stage symptoms to impact care earlier in the course of illness.

9:20 pm – 9:35 pm: Pro: The Severe Sepsis and Septic Shock Early Management Bundle (SEP-1) Bundle Saves Lives

- **Sean Townsend, MD (CPMC-Sutter)**- This speaker will argue the benefits of the SEP-1 Bundle/how it saves lives.

9:35 pm – 9:50 pm: Con: : The Severe Sepsis and Septic Shock Early Management Bundle (SEP-1) Bundle Does Not Save Lives

- **Natalie Achamallah, MD, MS (Cottage Health)** - This speaker will argue the against the SEP-1 Bundle/highlight its limitations.

9:50-10:00 am Question and Answer

10:00 am – 10:30 am: Break

Extracorporeal Membrane Oxygenation

10:30 am – 10:55 am: When to refer to an ECMO center and when to deploy ECMO

- **Nida Qadir, MD (UC Los Angeles)** - This speaker will discuss the evidence behind the use of ECMO in patients with respiratory failure and when providers should consider referral to an ECMO center and when centers should use ECMO.

10:55 am – 11:20 am: What about ECMO to go?

- **Mazen Odish, MD (UC San Diego)** - This speaker will discuss the advent of mobile ECMO services, how they can help improve patient care, and the use of extracorporeal cardiopulmonary resuscitation.

11:20 am – 11:45 pm: Ventilator Strategies for the patient on ECMO

- **Abirami Kumaresan, MD (Cedars-Sinai)** - This speaker will discuss the how ventilator strategies may differ in the patient on ECMO and how different ECMO configurations impact which ventilator strategy to use.

11:45 pm – 12:10 pm: What you need to know about pediatric ECMO

- **Kathleen Ryan, MD (Stanford)** - This speaker will discuss the utility of ECMO in neonates and children, and the complexities of management in children who needs mechanical support.

12:10 pm – 12:20 pm: Question and Answer

12:20 pm – 1:20 pm: Lunch

Hands-On Session:

1:20 pm – 2:20 pm: Non-Invasive Cardiac Output Monitors **Speaker Abirami Kumaresan, MD (Cedars-Sinai)** ECMO Machines **Mazen Odish, MD (UC San Diego)** ECMO Placement **David Gordon, DNP (UC San Francisco) & Brianna Zuckerman, NP (UC San Francisco)** Ventilator Settings and Portable ventilators **Joe Van Vleet, RT (UC Los Angeles) & Theresa Cantu, RT (Valley Children's)**

2:20 pm – 2:45 pm: Break

Inpatient and Pulmonary Complications of Cancer Care

2:45 pm – 3:10 pm: Pulmonary Complications of Hematopoietic Stem Cell Transplantation

- **Husham Sharifi, MD (Stanford)** - This speaker will discuss the pulmonary complications that arise after HCT, in particular the development of bronchiolitis obliterans syndrome and approaches to management.

3:10 pm – 3:35 pm: Pulmonary Vascular Complications of Malignancy

- **Naomi Habib, MD (Norton Thoracic Institute)**- This speaker will discuss the Pulmonary Vascular Disease complications of malignancy including PA sarcoma, pulmonary tumor thrombotic microangiopathy, and medications that can cause PAH.

3:35 pm – 4:00 pm: Drug induced Interstitial Lung Disease and Pneumonitis During Cancer Therapy

- **Weijia Chua, MD (Stanford)** - This speaker will discuss the pulmonary complications of interstitial lung disease and pneumonitis that develop after chemotherapy and targeted immunotherapy

4:00 pm – 4:25 pm: Respiratory Complications of Acute Leukemia

- **Hugh Davis, MD (City of Hope)** - The speaker will discuss various oncologic emergencies, how they are recognized, and how they are managed in the acute setting.

4:25 pm – 4:35 pm: Question and Answer

5:30 pm – 7:30 pm: Trainee Poster Competition (NON-CME) – Food and beverages will be served





Dr. Gabriel Wardi completed his undergraduate and graduate education in Atlanta. He moved to San Diego for his residency in Emergency Medicine where he served as chief resident during his final year of residency. He is the first graduate of the joint Critical Care Medicine fellowship offered by the Division of Pulmonary and Critical Care and Department of Emergency Medicine at UCSD. He joined the faculty in July 2017 and attends in both the emergency department and the ICUs at UCSD as an associate professor and founding Chief of the Division of Critical Care within the Department of Emergency Medicine. Dr. Wardi's research interests include sepsis, the ED-ICU interface, resuscitation, cardiac arrest management, and use of machine-learning to improve patient-centered outcomes. He is currently funded by the NIH to study how big data and machine-learning can improve outcomes of sepsis patients. He oversaw the clinical implementation of a novel deep-learning model to predict sepsis at UC San Diego Health, which resulted in a 17% relative decrease in sepsis-related mortality. He has received various awards for teaching and mentoring and has been selected as a "Top Doctor" in San Diego multiple times.



Incorporating Artificial Intelligence Decision Making in Identifying Sepsis

Gabriel Wardi, MD, MPH
Medical Director, Hospital Sepsis
University of California, San Diego

Disclosures

I have the following relationships with ACCME defined ineligible companies:

NONE.

I **WILL NOT** discuss off-label use and/or investigational use of any drugs or devices.

I report receiving funding from the National Institutes of Health, the National Foundation of Emergency Medicine, and consulting from Abbott Laboratories.

Objectives

Describe basics of artificial intelligence

Understand why AI is attractive for sepsis care

Recognize how AI can improve outcomes in sepsis care



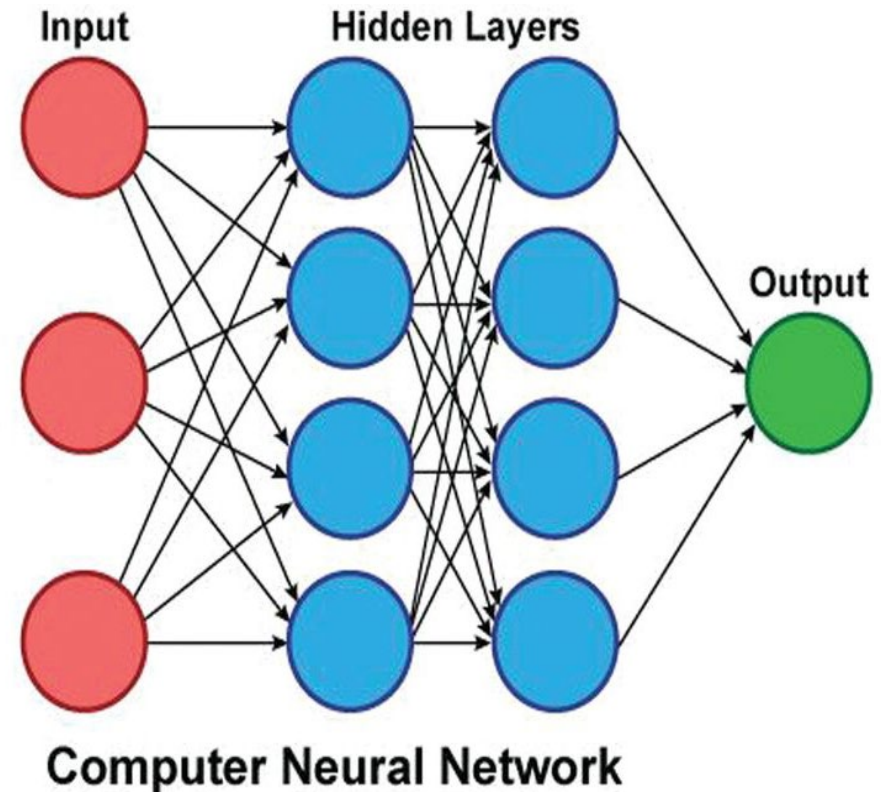


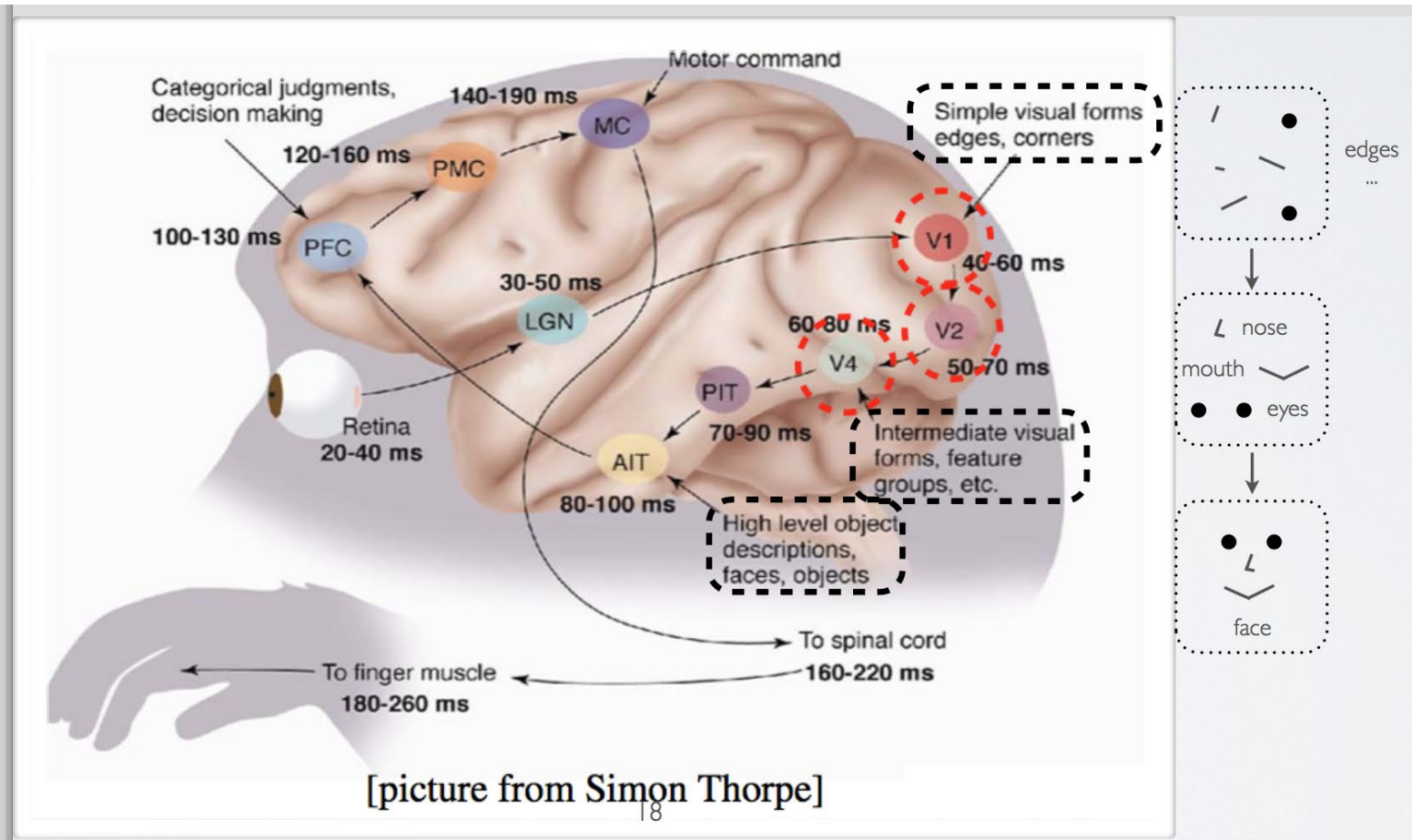
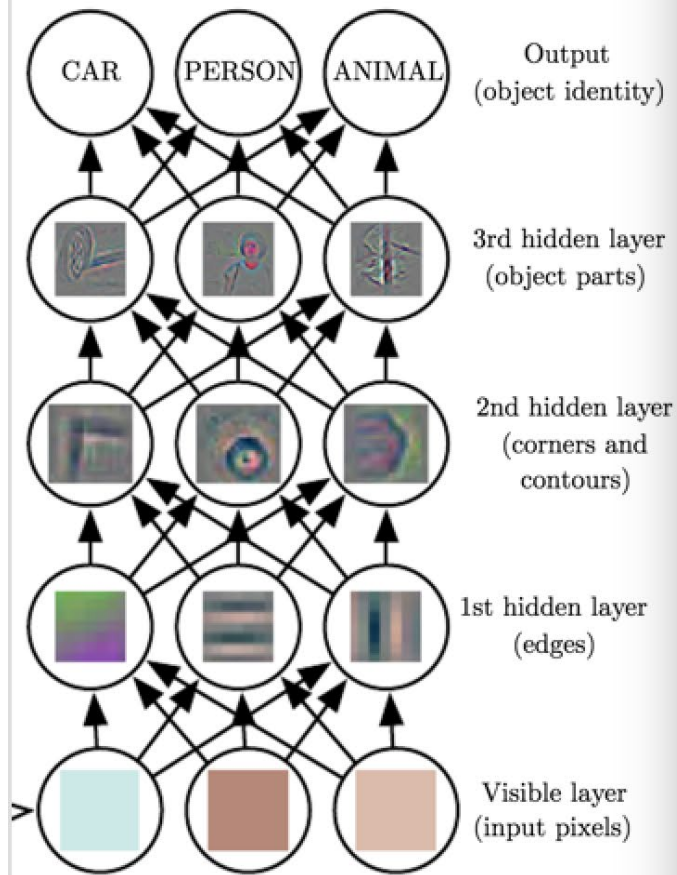
Understanding the Lingo

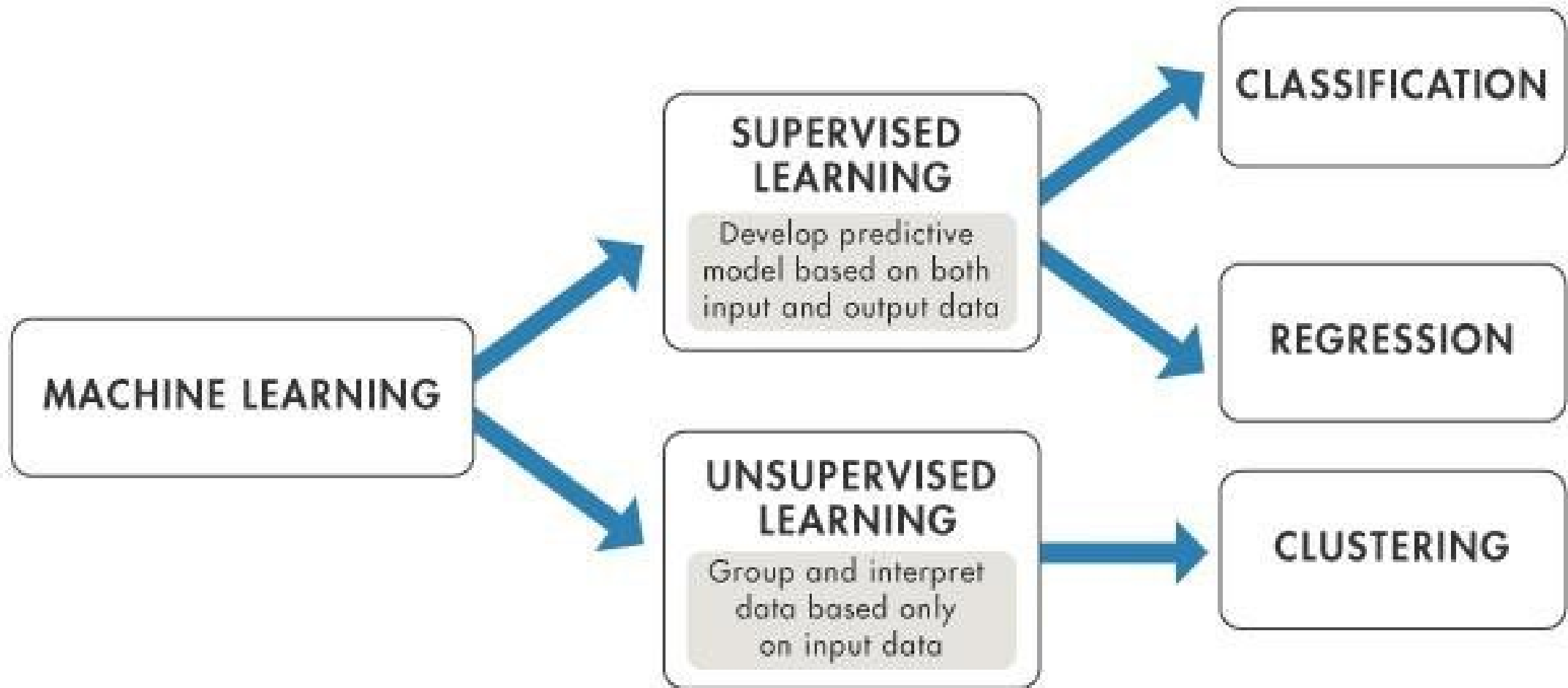
Artificial intelligence: loosely defined concept describing automated systems that can perform tasks considered to require “intelligence”

Machine learning: the process of developing systems with the ability to learn from and make predictions using data

Deep learning: group of ML methods that uses many layers of arithmetic operations





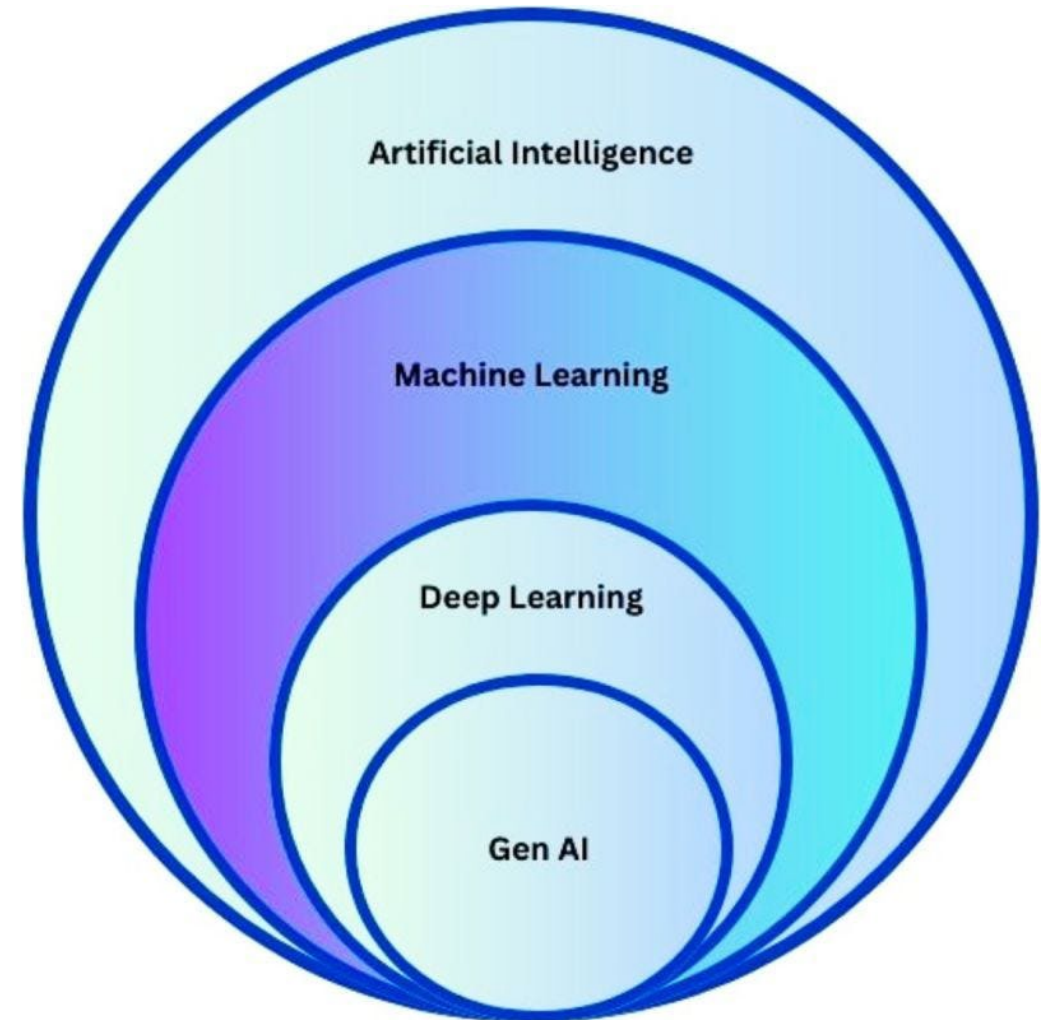


Generative AI

Class of machine learning that learns to generate new data from training data

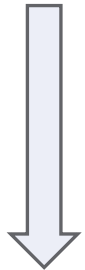
LLM is a subset of generative AI that uses natural language processing

Tremendous excitement for applications across medicine (and beyond)



What Can LLMs Do In Healthcare?

**Least
complex**



**Most
complex**

Data extraction	Chart review, patient safety reports
Translation	Translate instructions to another language, simplify patient education
Summarization	Write d/c summaries, sign-out & transitions of care
Generation	Provide differential diagnosis, chatbots, respond to patient messages

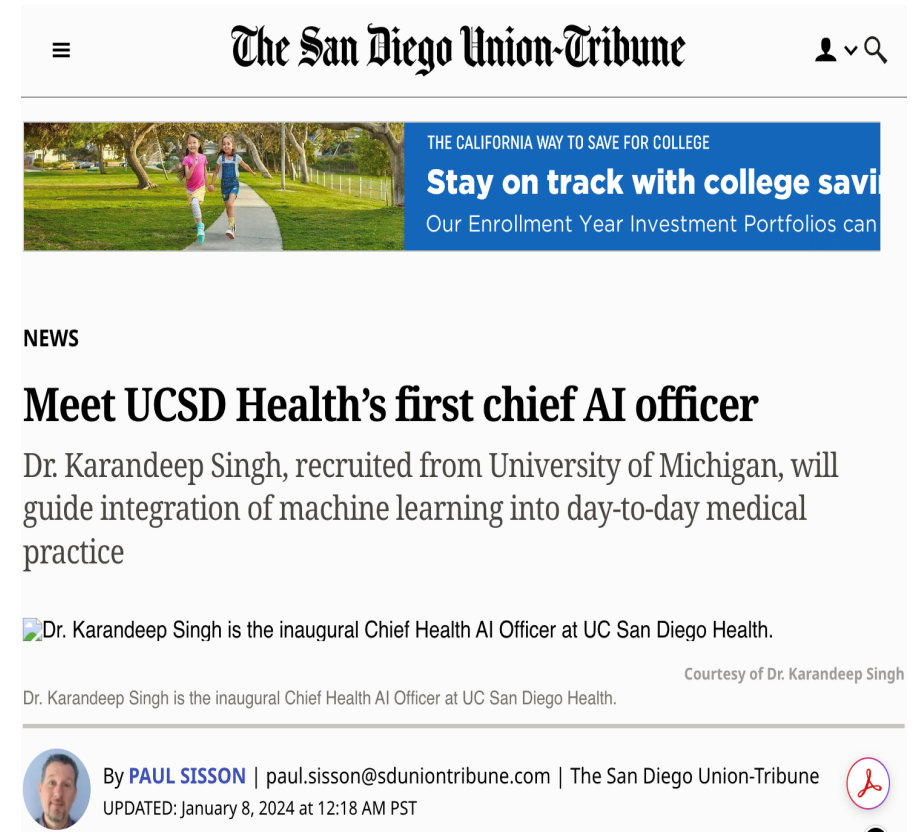
Why Are Physicians Excited?

Decreased time to diagnosis

Augmented therapeutic approaches

Time savings

Novel and exciting approach



The screenshot shows the top of a news article on the website 'The San Diego Union-Tribune'. At the top, there is a navigation bar with a hamburger menu icon on the left, the site name 'The San Diego Union-Tribune' in the center, and a user profile icon with a dropdown arrow and a search icon on the right. Below the navigation bar is a blue banner with a photo of two people jogging on a path. The banner text reads: 'THE CALIFORNIA WAY TO SAVE FOR COLLEGE Stay on track with college savi Our Enrollment Year Investment Portfolios can'. Below the banner is a 'NEWS' section. The main headline is 'Meet UCSD Health's first chief AI officer'. The sub-headline reads: 'Dr. Karandeep Singh, recruited from University of Michigan, will guide integration of machine learning into day-to-day medical practice'. Below the sub-headline is a small photo of Dr. Karandeep Singh and a caption: 'Dr. Karandeep Singh is the inaugural Chief Health AI Officer at UC San Diego Health.' To the right of the caption is the text 'Courtesy of Dr. Karandeep Singh'. At the bottom of the article snippet, there is a byline: 'By PAUL SISSON | paul.sisson@sduniontribune.com | The San Diego Union-Tribune' and an update timestamp: 'UPDATED: January 8, 2024 at 12:18 AM PST'. There is also a red circular icon with a white symbol on the right side of the byline.

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An Interpretable Machine Learning Model for Accurate Prediction of Sepsis in the ICU

Shamim Nemati, PhD¹; Andre Holder, MD, MSc²; Fereshteh Razmi, MS¹; Matthew D. Stanley, MD³; Gari D. Clifford, PhD^{1,4}; Timothy G. Buchman, PhD, MD^{3,5}



Supervised Machine Learning to Predict T_{sepsis} in ICU

Adult patients at Emory ICUs (n = 27,527) and MIMIC-3 database

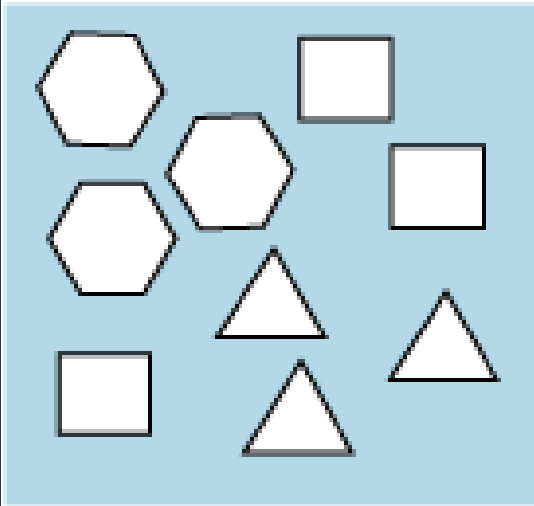
65 input features from EMR and available waveforms

Primary outcome: ability to predict sepsis 4– 12 hours of onset

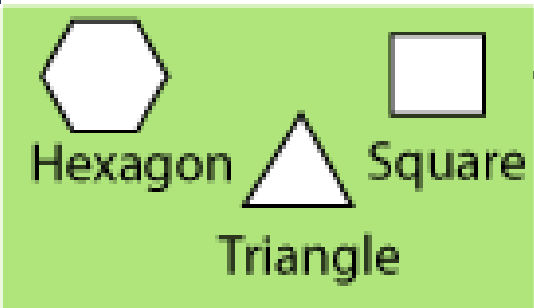
Modified Weibull-Cox proportional hazards model

HR, age, sex, lactate

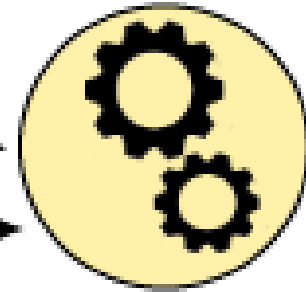
Labeled Data



Lables



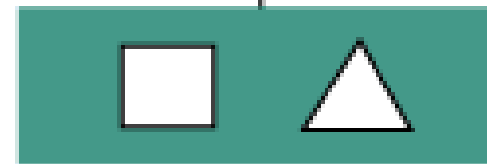
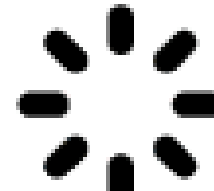
Sepsis



Model Training

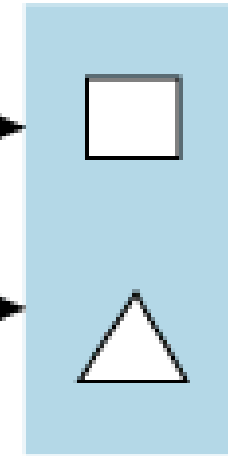
Modified Weibull-Cox
proportional hazards
model

Prediction



Test Data

New data set



Sepsis
Square

Triangle
Not sepsis

Evaluate model
performance

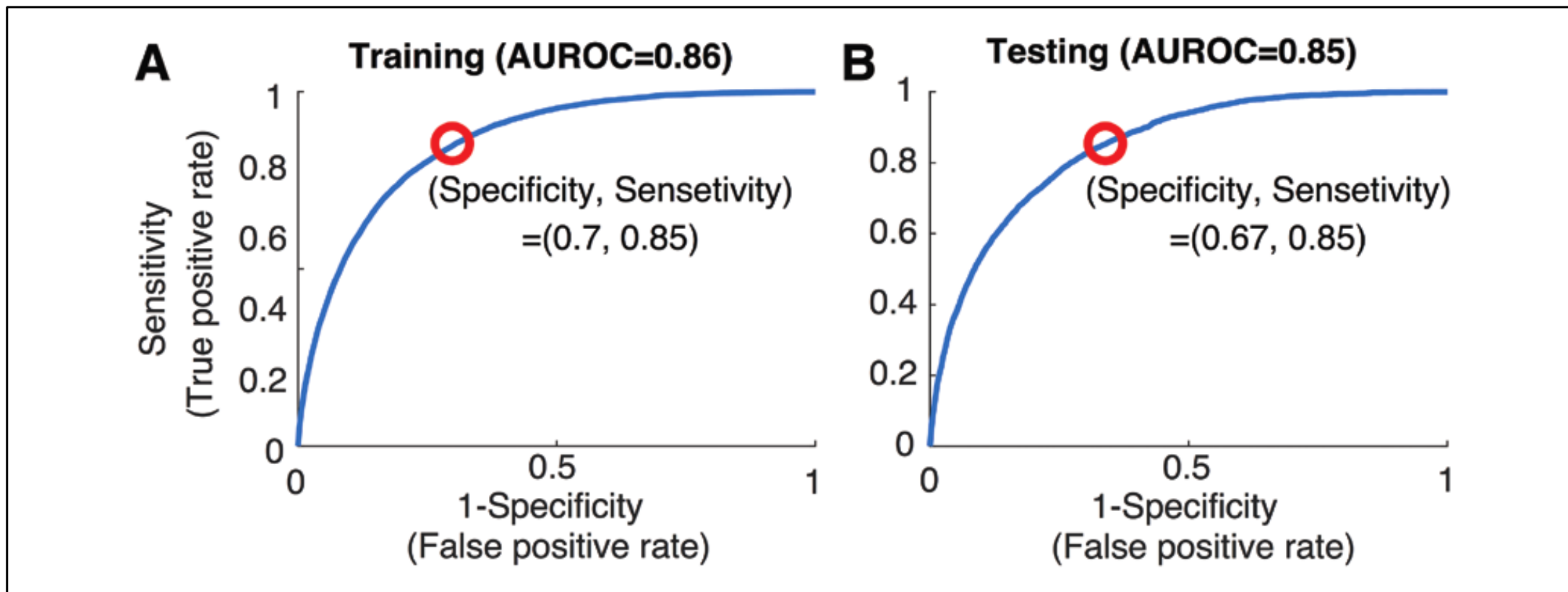


Figure 1. Area under the receiver operating characteristic (AUROC) curves for predicting t_{sepsis} 4 hr in advance. Catching 85% of the septic patients yielded 30% false alarms (specificity = 0.70) within the training set (**A**) and 33% false alarms (specificity = 0.67) within the testing set (**B**). See Table 2 for information on the false alarms.

Takeaways from *Nemati, et al.*

Retrospective observational study

Good model performance in ICU based on AUC

False positives with high mortality

Implementation and generalizability unaddressed

Derivation, Validation, and Potential Treatment Implications of Novel Clinical Phenotypes for Sepsis

Christopher W. Seymour, MD, MSc; Jason N. Kennedy, MS; Shu Wang, MS; Chung-Chou H. Chang, PhD; Corrine F. Elliott, MS; Zhongying Xu, MS; Scott Berry, PhD; Gilles Clermont, MD, MSc; Gregory Cooper, MD, PhD; Hernando Gomez, MD, MPH; David T. Huang, MD, MPH; John A. Kellum, MD, FACP, MCCM; Qi Mi, PhD; Steven M. Opal, MD; Victor Talisa, MS; Tom van der Poll, MD, PhD; Shyam Visweswaran, MD, PhD; Yoram Vodovotz, PhD; Jeremy C. Weiss, MD, PhD; Donald M. Yealy, MD, FACEP; Sachin Yende, MD, MS; Derek C. Angus, MD, MPH



Unsupervised Learning to Create Phenotypes

Data from 3 observational cohorts and 3 RCTs (n = 87,844)

Used 29 variables (age, inflammatory markers, organ failure)

Biologic data from 27 biomarkers of host response

Consensus k means clustering to assign phenotypes

29 Clinical Variables

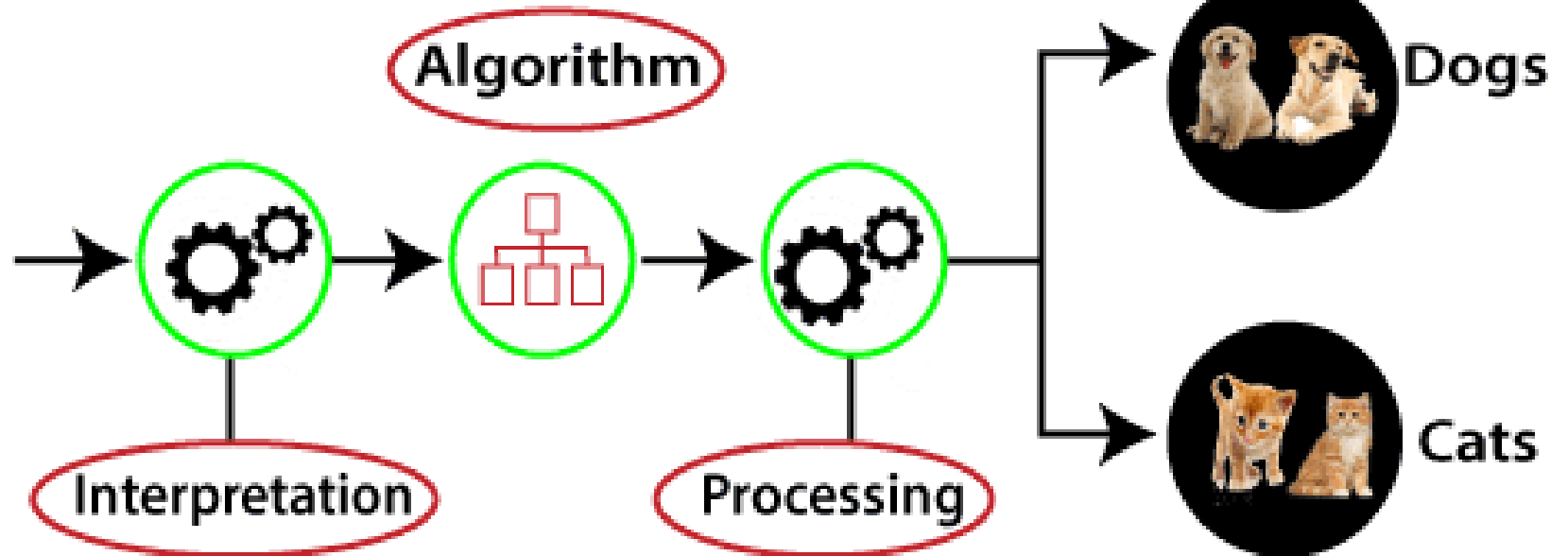
Sepsis Phenotypes

INPUT RAW DATA

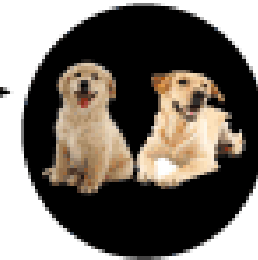


Unlabeled data

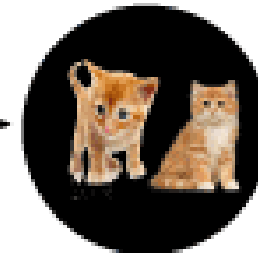
Consensus k means clustering algorithm



OUTPUT

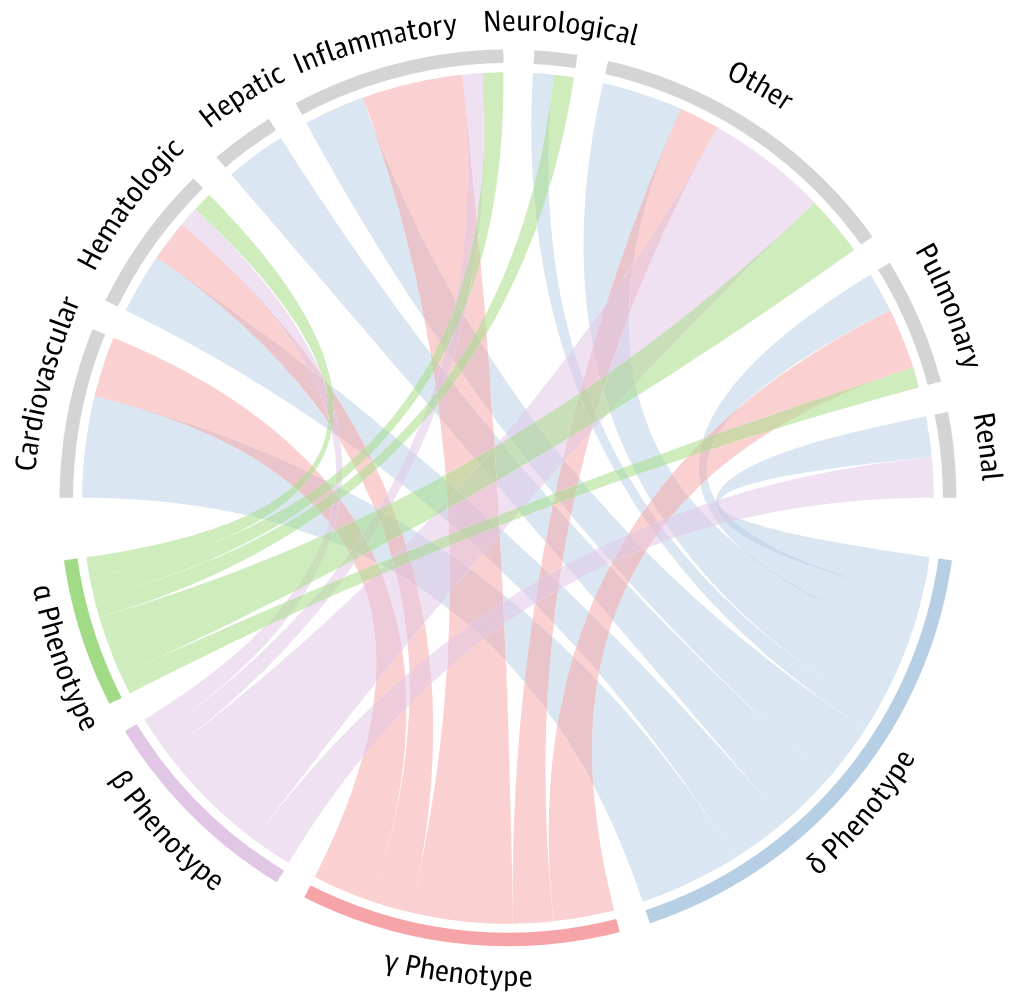


Dogs

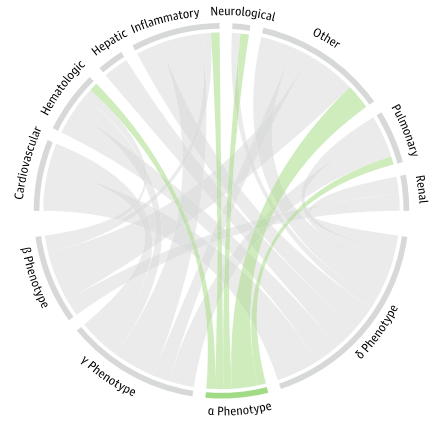


Cats

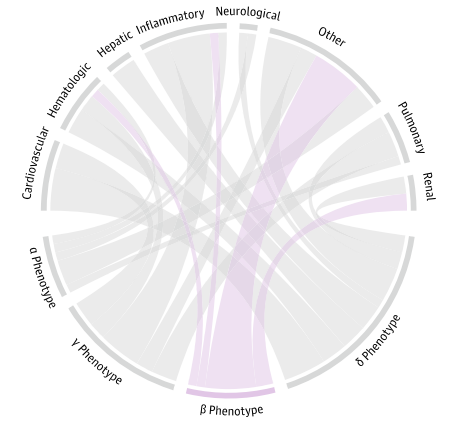
A All phenotypes combined



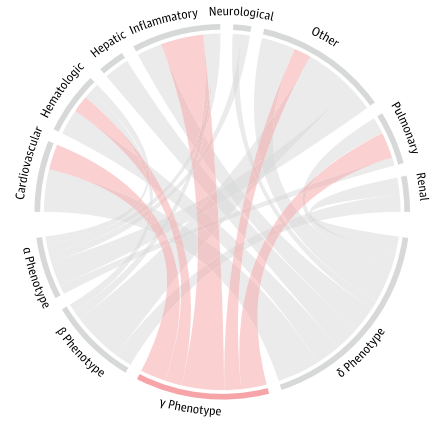
B α Phenotype



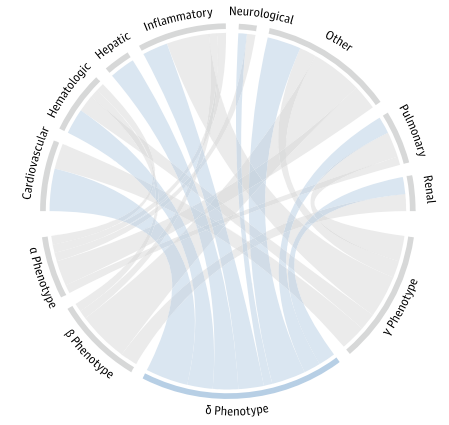
C β Phenotype



D γ Phenotype



E δ Phenotype



Takeaways from *Seymour, et al.*

Clinical phenotypes demonstrated with biologic confirmation

Potential harm in certain patients from fluid resuscitation

Retrospective study although large dataset

External validation of phenotypes has struggled

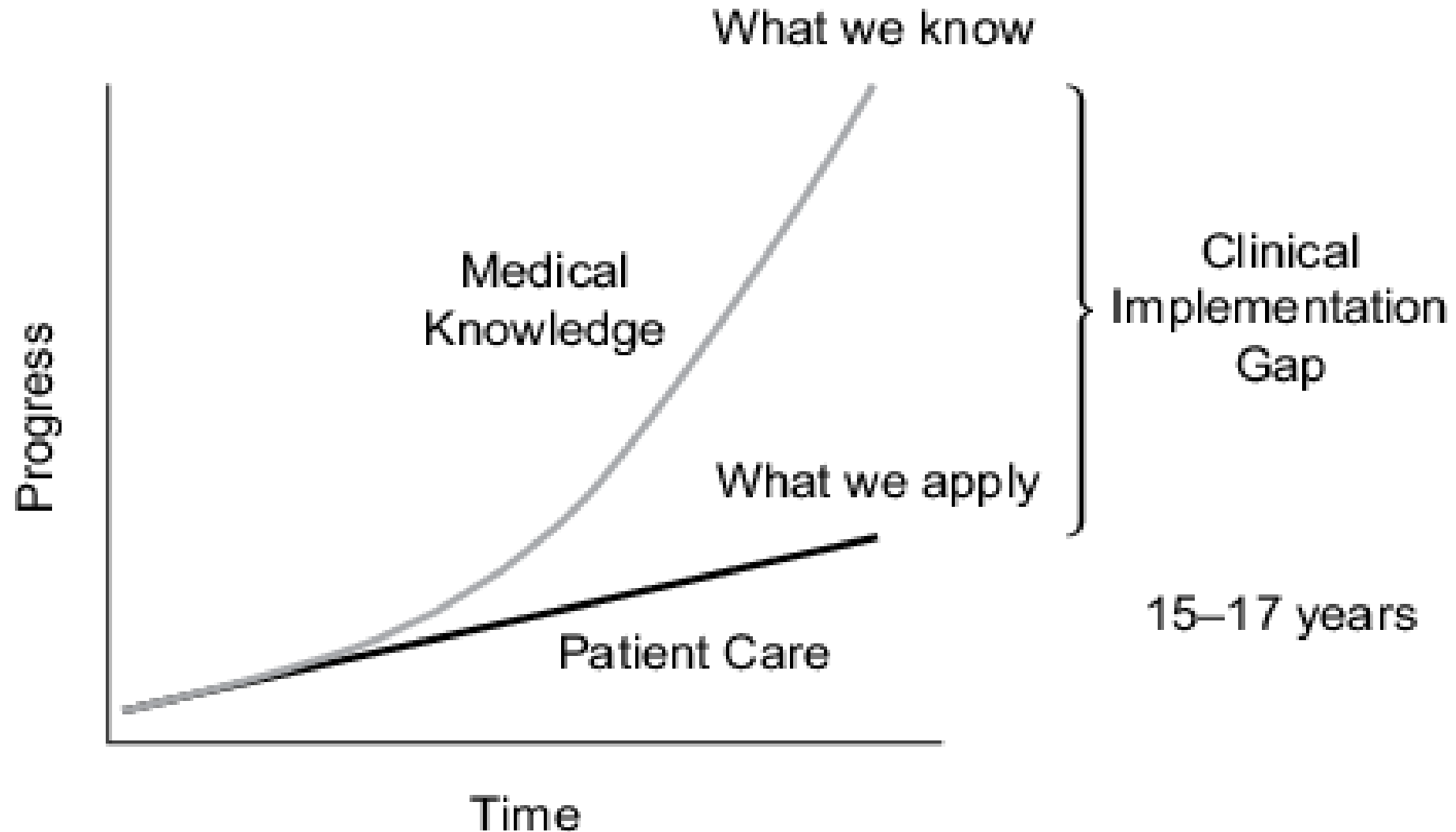
Objectives

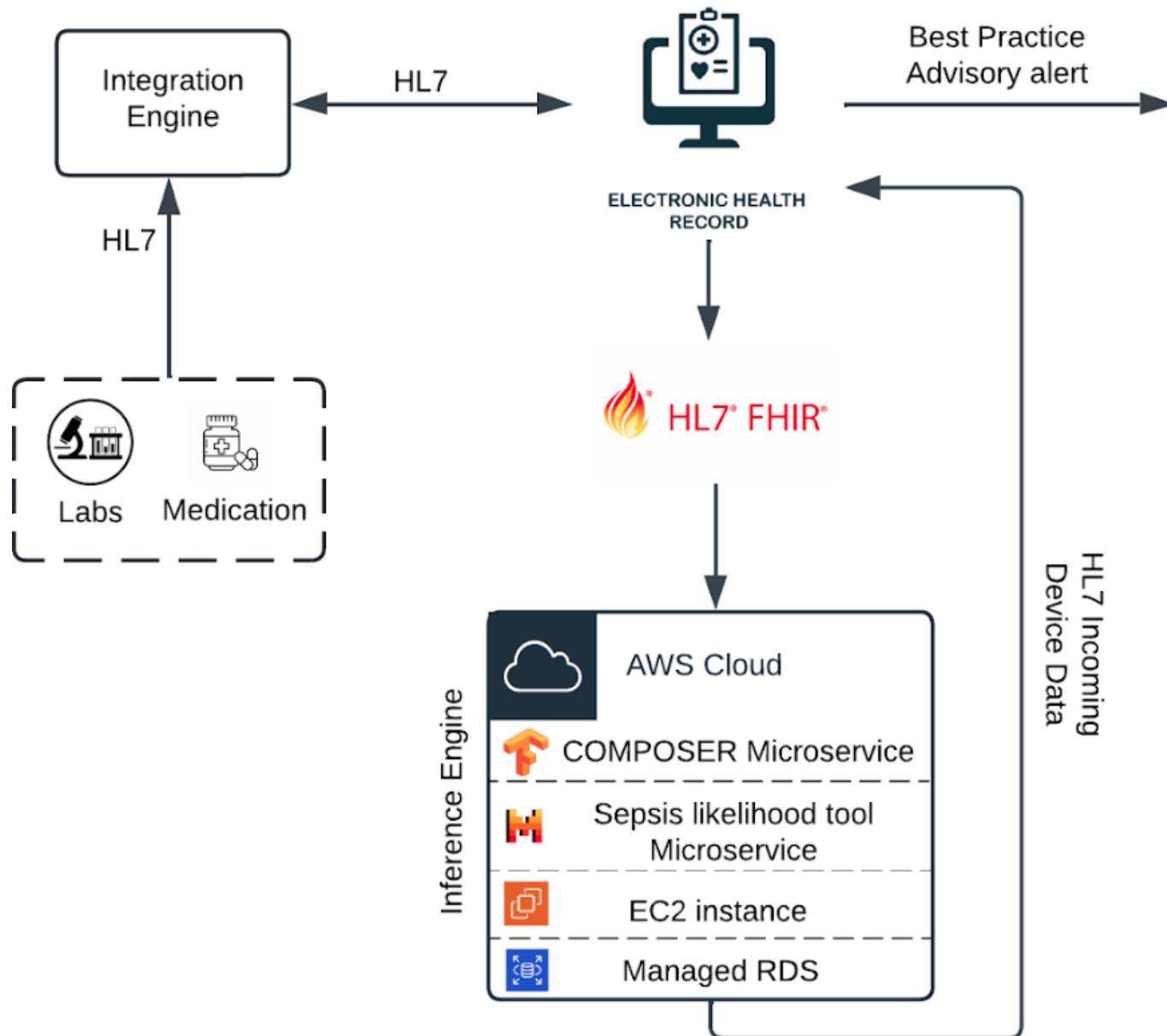
Describe basics of artificial intelligence

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Clinical Implementation Gap





The EPIS Framework

Strategic and operational implementation activities



Evaluate the needs fit and resources required
Create a strategy

Prepare the people (inc. leaders/managers), organisation & resources including:
Systems, knowledge/expertise, skills, policies, procedures

Start enacting EBP using feedback, evidence, internal and external knowledge and skills

Workout how to sustain EBP in & across the organisation

FIRM USE CASE SCENARIO:
Sepsis not obvious

CMO/MD/RN LEADERSHIP BUY-IN:
Epic staff and Quality Department

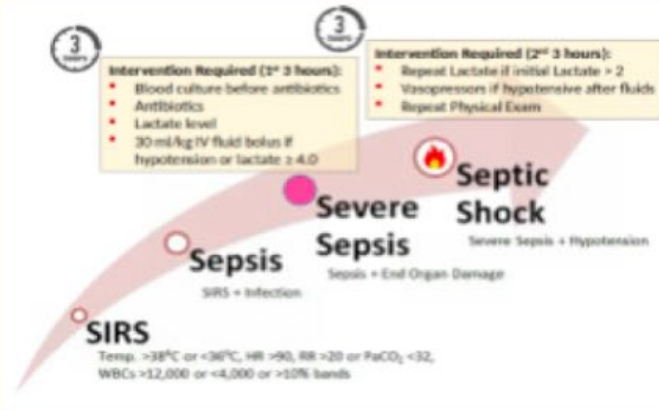
CONTINUAL FEEDBACK, EDU:
Survey data, serial "just in time" visits

CONTINUAL IMPROVEMENTS:
Individual feedback, frequent updates, and analysis

Emergency (1)



⚠️ Could it be Sepsis?



This patient has a Sepsis Risk Score:
90% chance of developing severe sepsis
in the next 4 hours.

Consider discussing risk of sepsis with the
primary physician or activating Code Sepsis

Top reasons in the past 6 hours

Sepsis Top Causes: Temperature, Heart Rate

Order

Do Not Order

👉 SUSPECTED SEPSIS STANDING ORDERS

👉 [Secure Chat the Physician and Dr. Gabe Wardi](#)

The following actions have been applied: _____

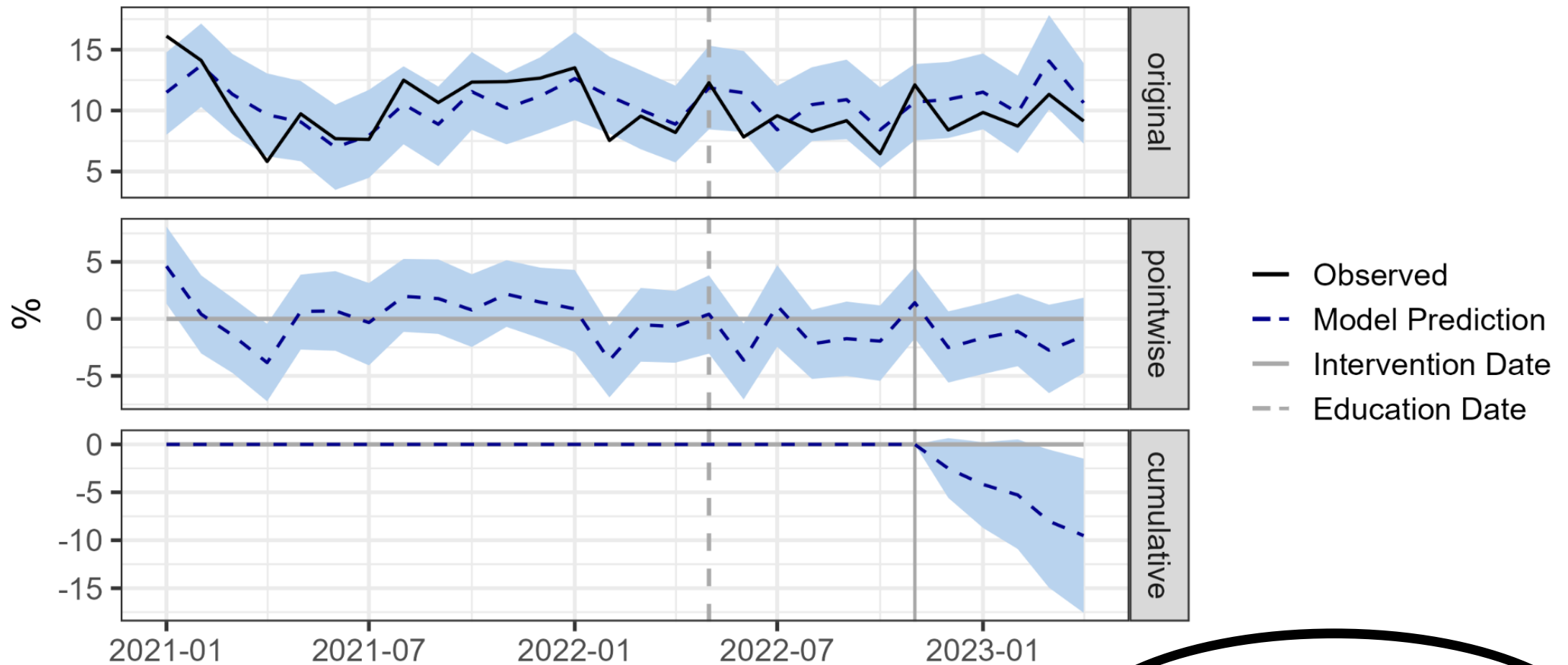
✓ Sent: 🔔 A summary of this advisory has been sent as a push notification

⚠️ Acknowledge Reason _____

No Infection Suspected

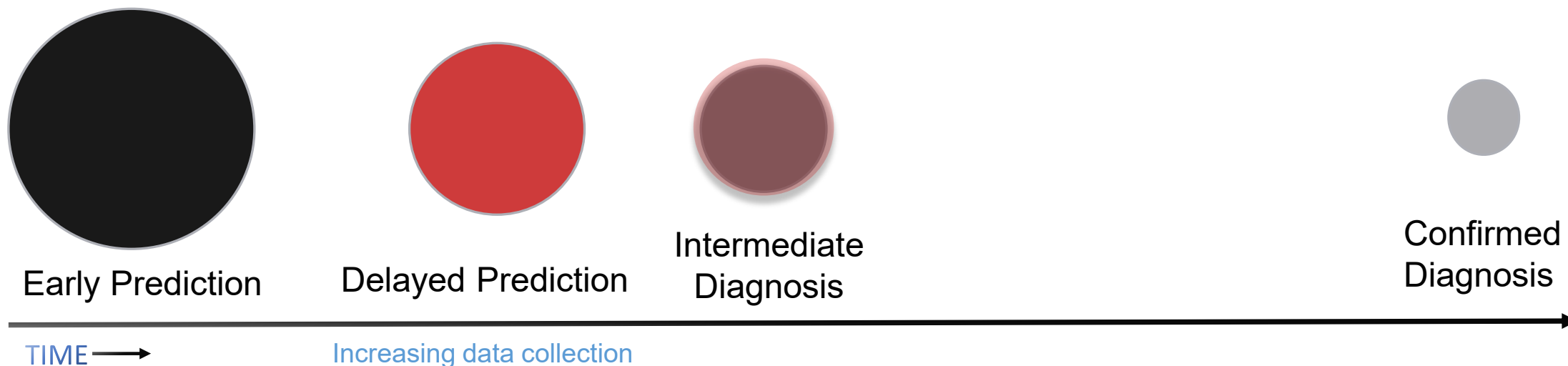
Will Notify MD Immediately

Sepsis Treatment/Workup in Progress



1.9% absolute decrease or
17% relative decrease in
mortality

Clinicians Deal with Diagnostic Uncertainty Daily, Why Can't AI?



- Lack of availability of timely data
 - "Data deserts" common in health care
- Multiple potential explanations for the observed signs and symptoms
 - Lack of clinical context (patient history)
- Limited knowledge of system-level mechanisms & relevant measurements

Multi-Modal Data

Multimodal data = multiple forms of data used together

Potential to significantly improve decision making

Ex: LLMs; wearable devices; imaging studies; patient-facing chatbots

INVITED FOREWORD

OPEN

Bringing the Promise of Artificial Intelligence to Critical Care: What the Experience With Sepsis Analytics Can Teach Us

KEY WORDS: artificial intelligence; critical care; deep learning; machine learning; sepsis

In 1985, development of a computer system called “Deep Thought” began at Carnegie Mellon University with the lofty objective of developing an autonomous system capable of outperforming the world’s top chess grandmasters. Later renamed “Deep Blue,” this chess-playing expert system defeated world champion Gary Kasparov in 1997 in a six-game match. However, it was not until 2017 that a deep artificial neural network algorithm known as “AlphaZero” achieved super-human performance in several challenging games, including Chess, Shogi, and Go (1). Such triumphs in computer-based technologies are common today as artificial intelligence (AI) applications, such as ChatGPT and DALL-E, are mimicking human capabilities, even passing medical board examinations (2). The term AI is used to describe the general ability of computers to emulate various characteristics of human intelligence, including pattern recognition, inference, and sequential decision-making, among others. Machine learning (ML) is a subset of AI that can learn the complex interactions or temporal relationships among multivariate risk factors without the need to hand-craft such features via expert knowledge (3). Retrospective studies have demonstrated ML applications are particularly useful for their diagnostic and prognostic capabilities leveraging vast quantity of data available in the ICU (4, 5). Certain ML algorithms have approached human performance at narrow tasks such as predicting resuscitation strategies in sepsis (6), need for mechanical ventilation (7), mortality in critically ill patients (8), and ICU length of stay (9).

Sepsis is an attractive target for ML approaches as it is an inherently complex, common, costly, and deadly condition. Prediction of sepsis is the most common ML application described, although recent advances include approaches to optimize therapeutics and resuscitation strategies (6, 10). Given the potential to improve patient-centered outcomes and excitement about newer analytic approaches, it is no surprise that the number of ML algorithms aimed to improve sepsis care is increasing at a rapid rate. However, errors in sepsis prediction are often highlighted both in anecdotal and health system-wide failures that can be traced to poor implementation approaches, rudimentary ML algorithms, application of algorithms outside their intended use, or without proper maintenance. Noting these criticisms, what can be done at this point to demonstrate value of these predictive models? We believe that a revised focus on data enrichment, proper implementation, and rigorous testing is required to bring the promise of AI to the ICU.

Gabriel Wardi, MD, MPH^{1,2}
Robert Owens, MD²
Christopher Josef, MD³
Atul Malhotra, MD²
Christopher Longhurst, MD⁴
Shamim Nemat, PhD⁵

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DOI: 10.1097/CCM.0000000000005894

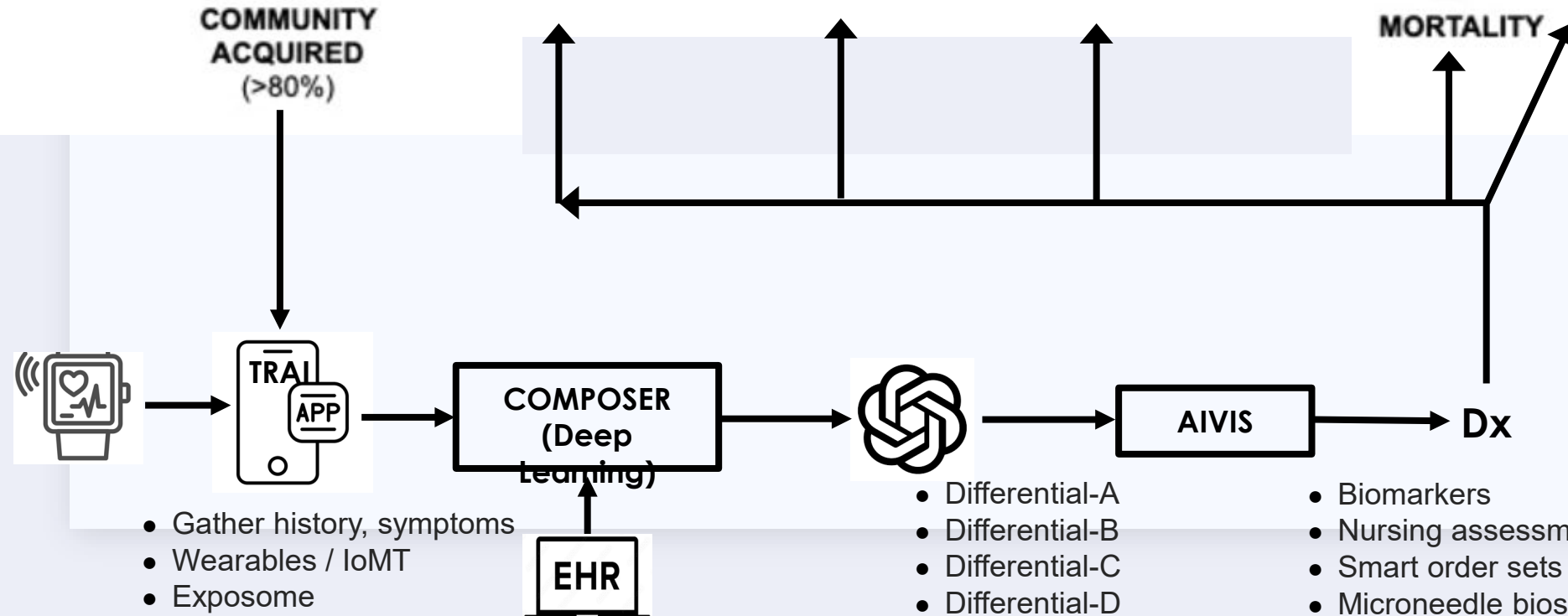
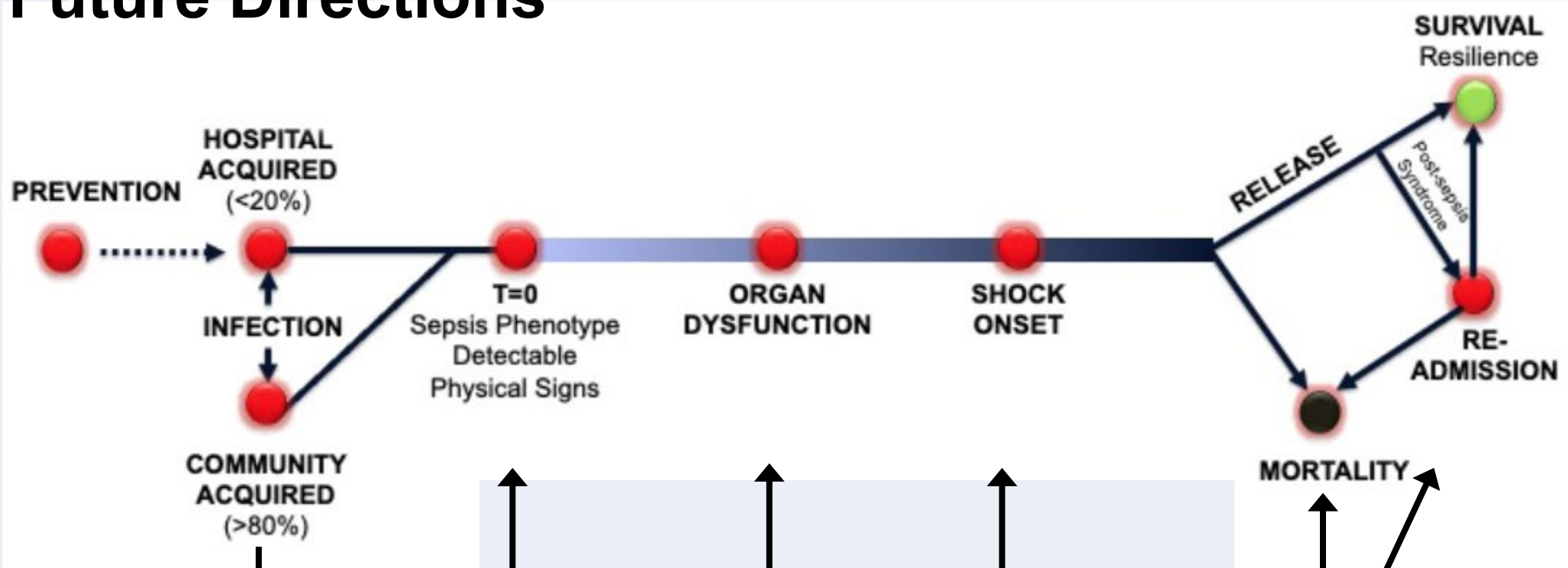
Uncertainty, Sepsis Mimics, and DDx

Clinical notes allow for context

LLMs can ingest notes for augmented predictive abilities

Our data show no sacrifice in sensitivity

Future Directions



- Gather history, symptoms
- Wearables / IoMT
- Exposome

- Differential-A
- Differential-B
- Differential-C
- Differential-D

- Biomarkers
- Nursing assessments
- Smart order sets
- Microneedle biosensors



Microneedle sensors for analytes (e.g., lactate)



Inflammatory biomarkers pathogen profiling

Conclusions

Sepsis remains a public health emergency which may benefit from machine-learning approaches

Understanding terminology / intended use is critical

Future endeavors need to bridge the development-to-implementation gap