Artificial intelligence in the ICU

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Conflict of interest

Multicenter, randomized, controlled trials evaluating mortality in intensive care: Doomed to fail?

Gustavo A. Ospina-Tascón, MD; Gustavo Luiz Büchele, MD; Jean-Louis Vincent, MD, PhD

Objectives: To determine how many multicenter, randomized controlled trials have been published that assess mortality as a primary outcome in the adult intensive care unit population, and to evaluate their methodologic quality.

Data Source: A sensitive search strategy for randomized controlled trials was conducted in the Cochrane Central Register of Controlled Trials and in MEDLINE using the PubMed interface.

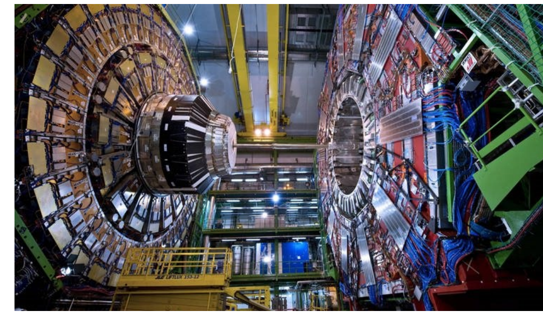
Study Selection: All publications of adult, multicenter randomized controlled trials carried out in the intensive care unit, with mortality as a primary outcome, and including >50 patients were selected.

Data Extraction: Seventy-two randomized controlled trials were retrieved and were classified according to their effect on mortality: beneficial, detrimental, or neutral.

Data Synthesis: Ten of the studies reported a positive impact of the studied intervention on mortality, seven studies reported a detrimental effect of the intervention, and 55 studies showed no effect on mortality.

Conclusions: This literature search demonstrates that relatively few of the randomized controlled trials conducted in intensive care units and using mortality as a primary outcome show a beneficial impact of the intervention on the survival of critically ill patients. Methodological limitations of some of the randomized controlled trials may have prevented positive results. Other forms of evidence and end points other than mortality need to be considered when evaluating interventions in critically ill patients. (Crit Care Med 2008; 36:1311–1322)

KEY WORDS: mortality; outcome; critically ill



10 studies
decreased mortality

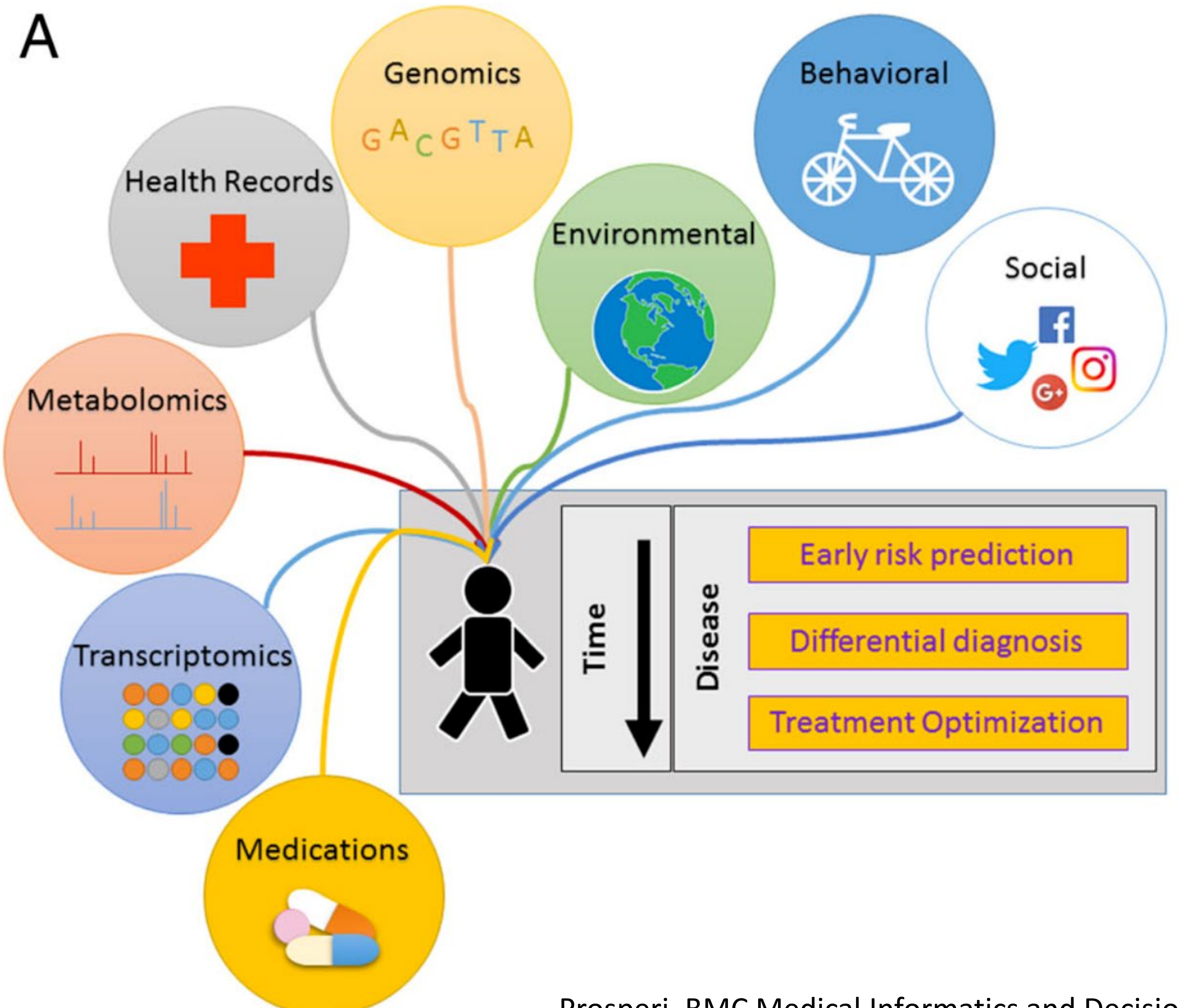
7 studies
increased mortality

55 studies no effect

RCTs: One size fits all!

AI enables personalized medicine

The number one use case in medicine: categorization and prediction



Prosperi, BMC Medical Informatics and Decision Making, 2018

What has been published in the last years?

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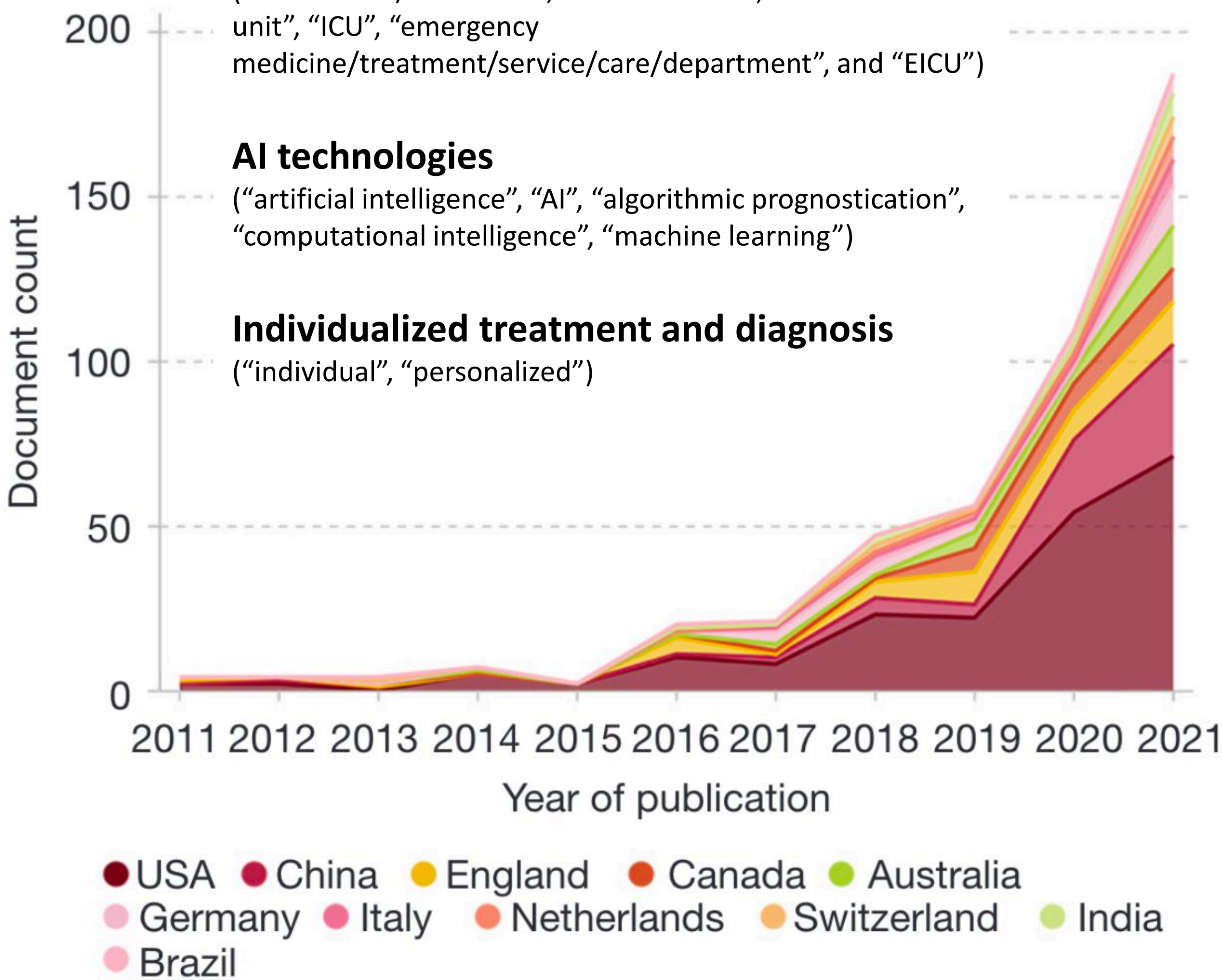
Critical illness
(“critical care/treatment”, “intensive care”, “intensive care unit”, “ICU”, “emergency medicine/treatment/service/care/department”, and “EICU”)

AI technologies
(“artificial intelligence”, “AI”, “algorithmic prognostication”, “computational intelligence”, “machine learning”)

Individualized treatment and diagnosis
(“individual”, “personalized”)



Liu, Ann Transl Med, 2022

What has been published in the last years?

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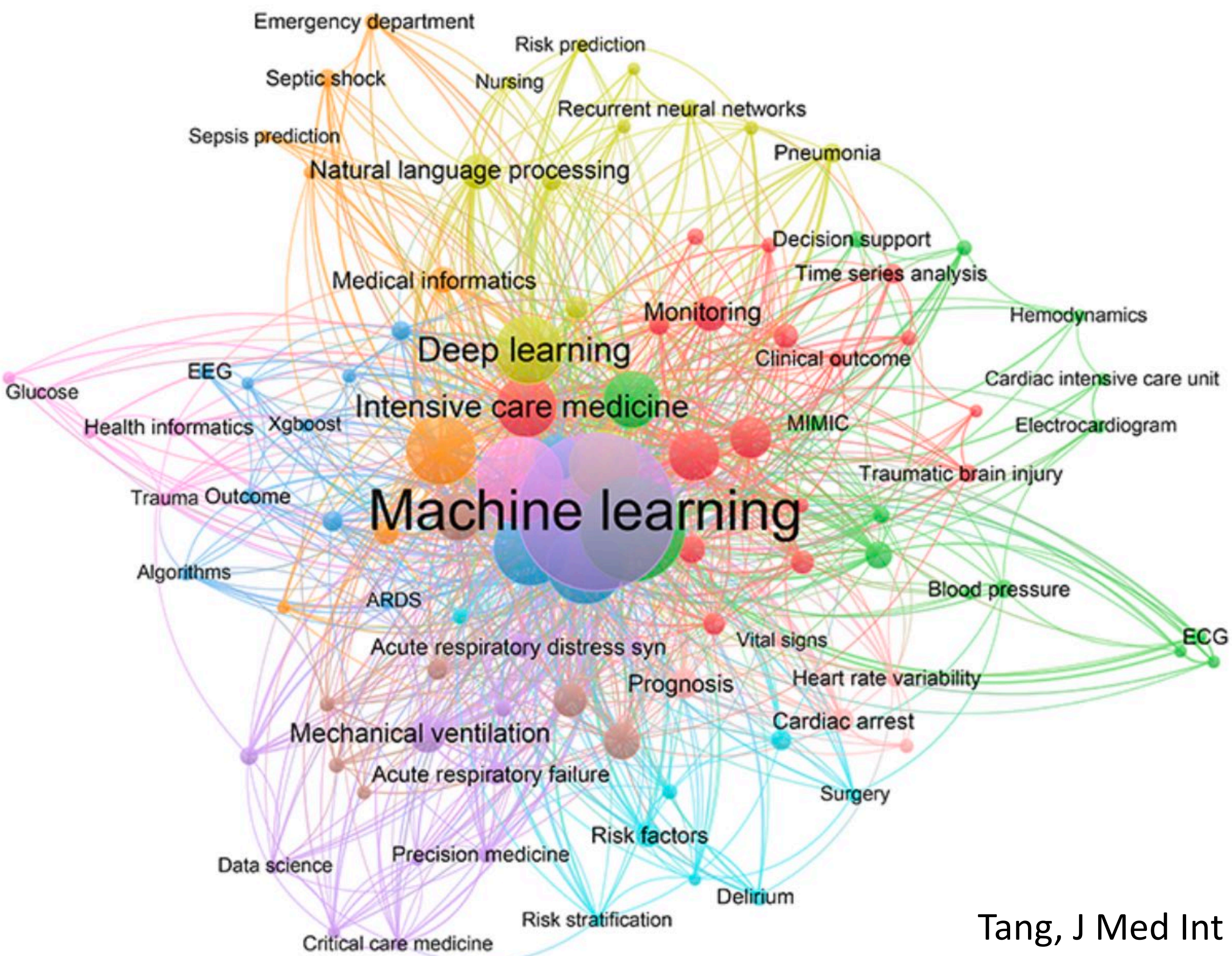
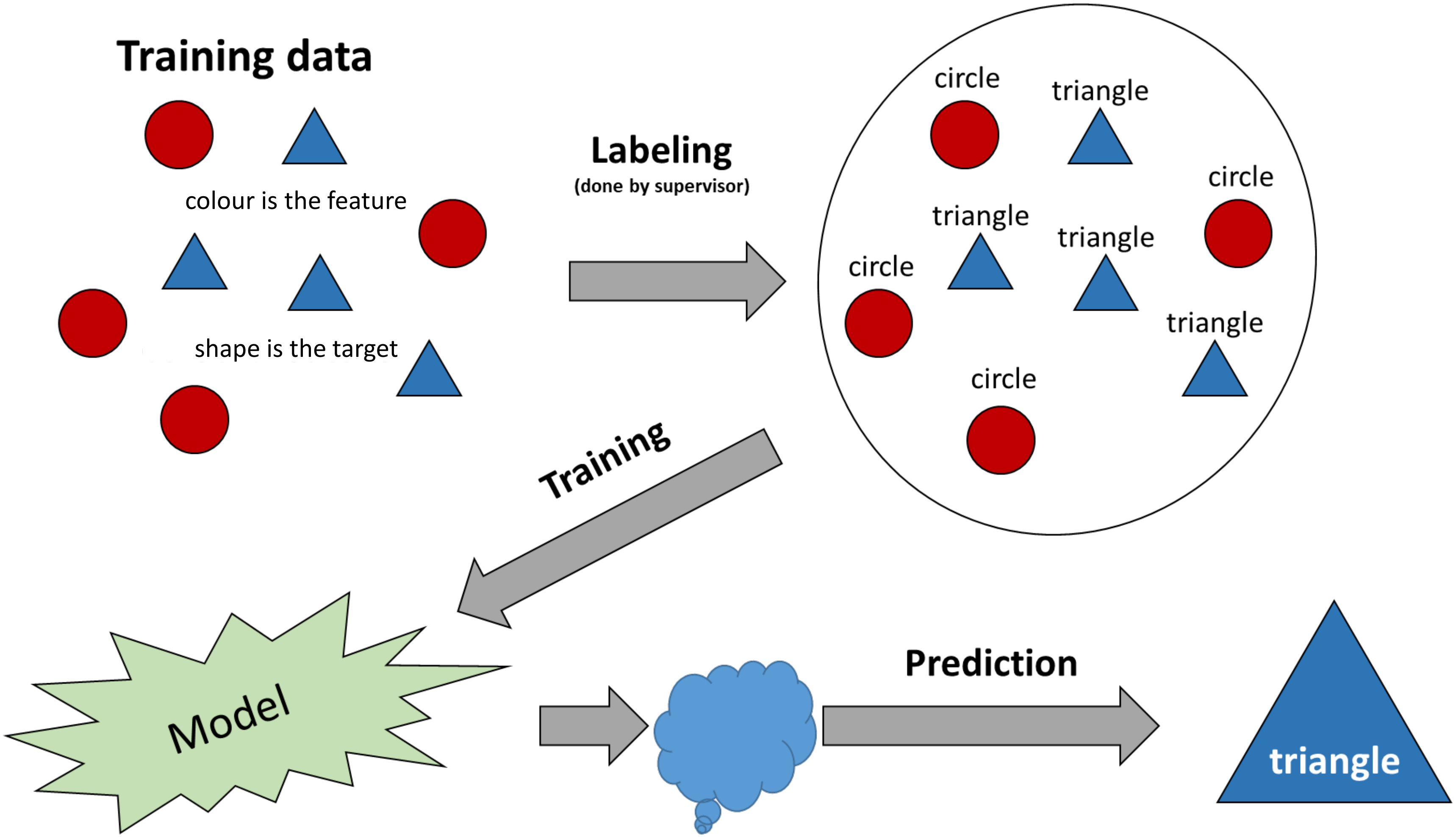
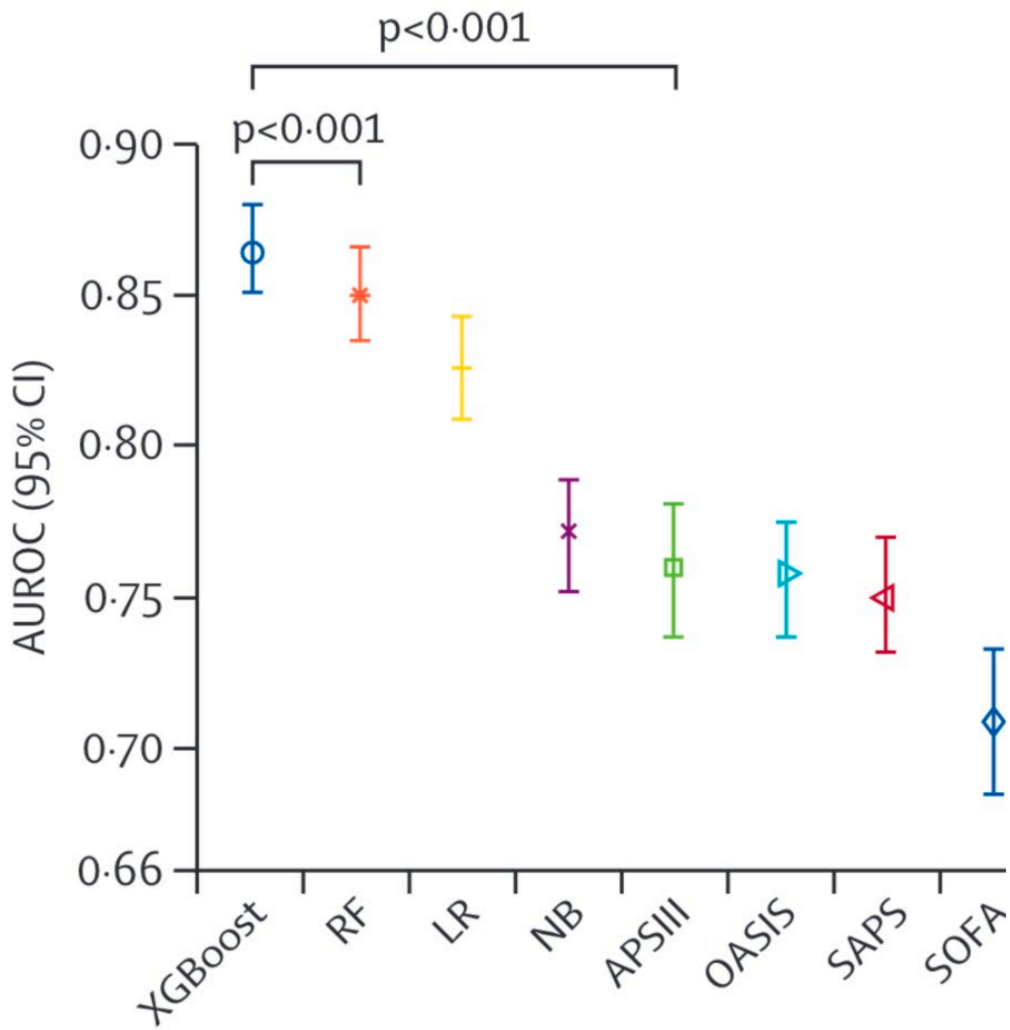


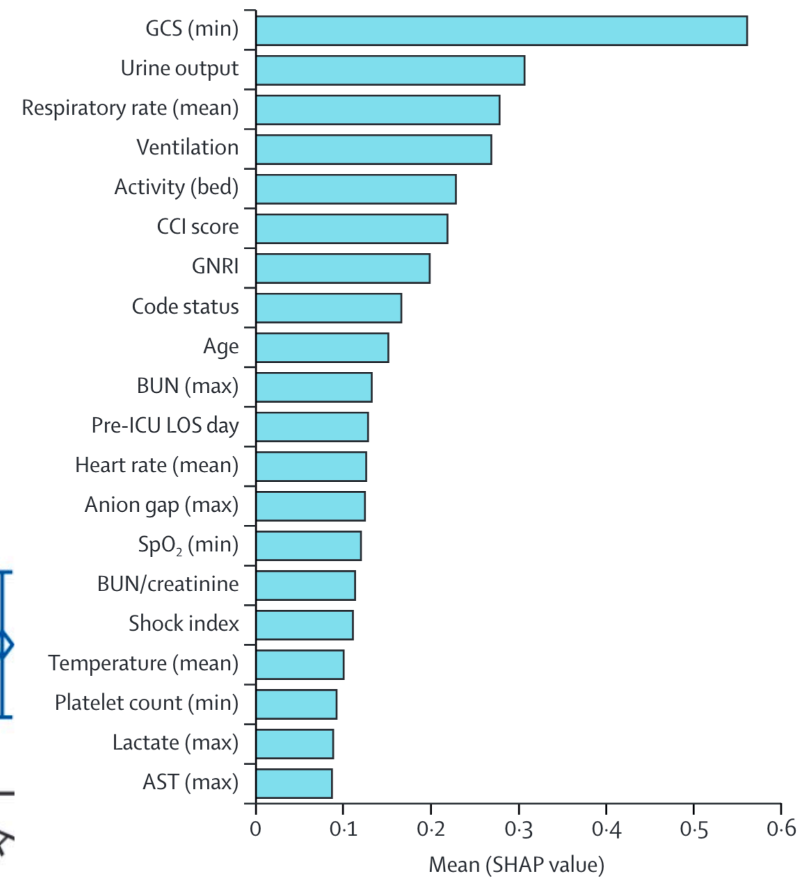
Tang, J Med Int Res, 2022

Supervised machine learning



Prediction of ICU mortality





Ishii, Anaesth Crit Care Pain Med, 2023

Yu *et al. BMC Medical Informatics and Decision Making* (2024) 24:223
https://doi.org/10.1186/s12911-024-02629-6

BMC Medical Informatics and Decision Making

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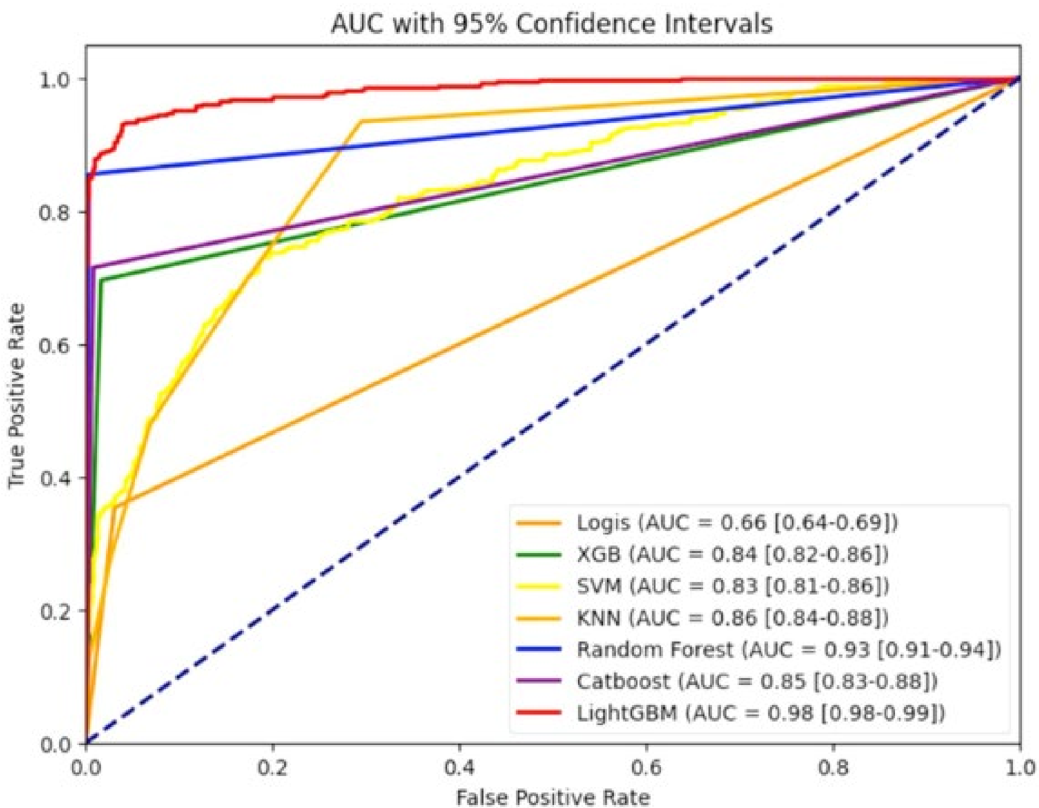
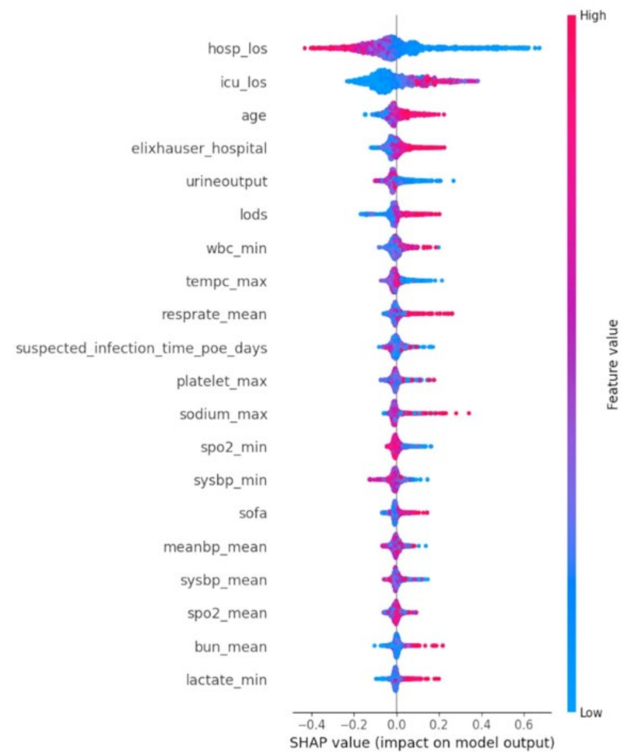
RESEARCH **Open Access**

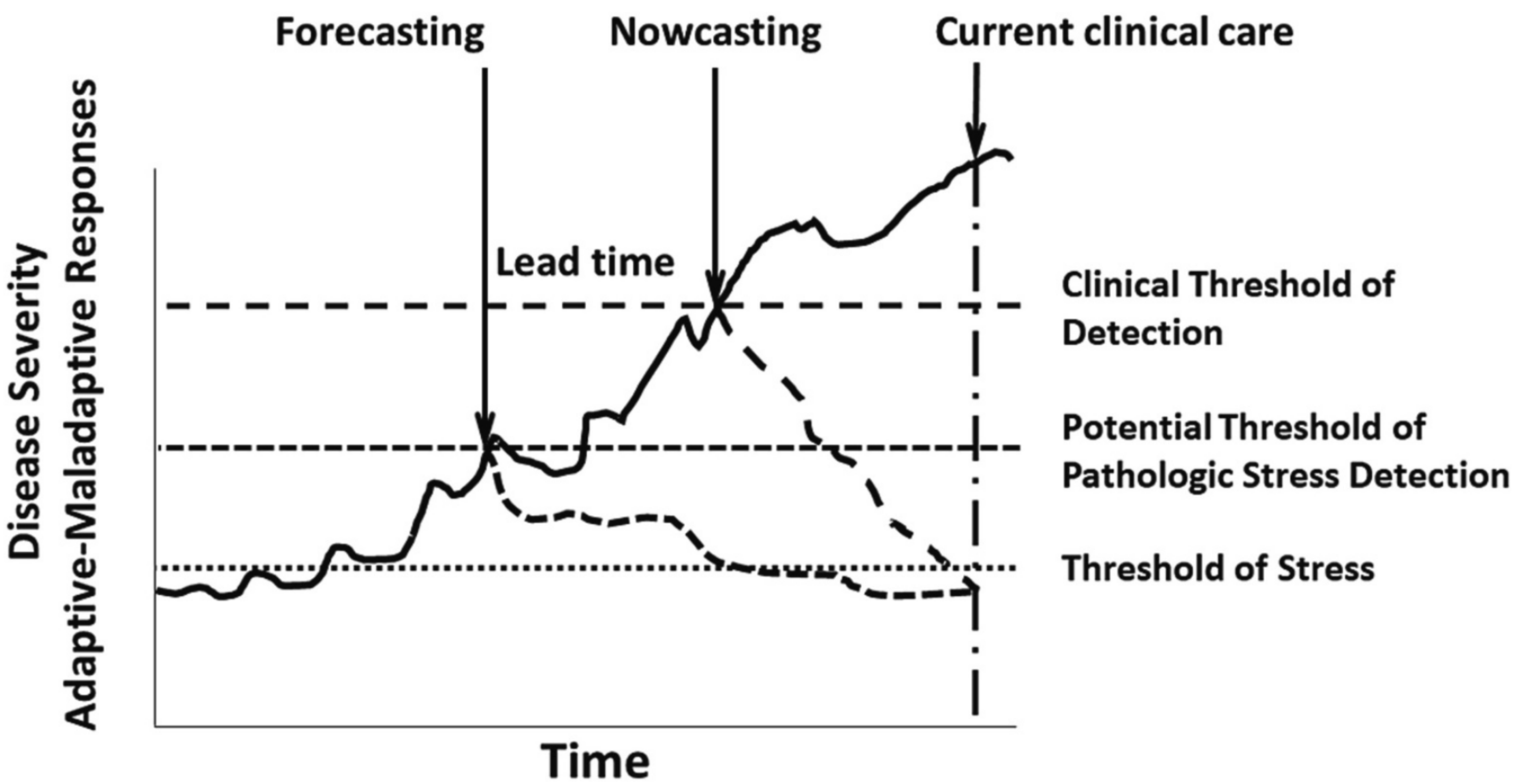
Prediction of 30-day mortality for ICU patients with Sepsis-3

Zhijiang Yu[1], Negin Ashrafi[1], Hexin Li[1], Kamiar Alaei[2] and Maryam Pishgar[1*]





Forecasting in the ICU

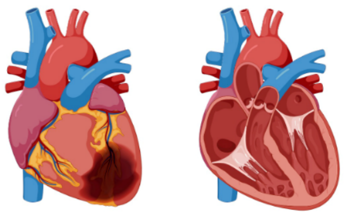


Rooney, J Electrocard, 2023

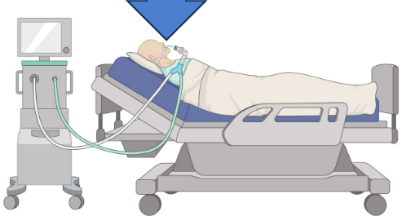
Prediction of cardiogenic shock at the ICU

Myocardial Infarction

Heart Failure



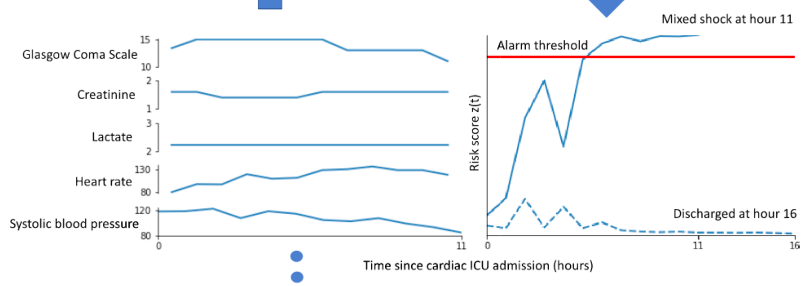
Early detection of cardiogenic shock is critical for improving patients' outcomes but has been challenging



Cardiogenic Shock

CShock uses dilated, causal CNN for early prediction of cardiogenic shock

CShock risk model



Development dataset

MIMIC

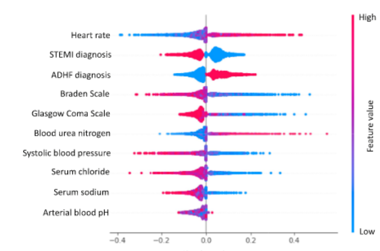
External validation dataset

NYU Langone Health

	CShock AUROC
MIMIC-III	0.821 (95% CI 0.792-0.850)
NYU	0.800 (95% CI 0.717-0.884)

CShock can predict cardiogenic shock >*37* hours ahead of the shock event

Top 10 features in CShock model in descending order of importance



Hu, EHJ, 2024

Forecasting of MAP

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Machine-learning Algorithm to Predict Hypotension Based on High-fidelity Arterial Pressure Waveform Analysis

Feras Hatib, Ph.D., Zhongping Jian, Ph.D., Sai Buddi, Ph.D., Christine Lee, M.S., Jos Settels, M.S., Karen Sibert, M.D., F.A.S.A., Joseph Rinehart, M.D., Maxime Cannesson, M.D., Ph.D.

ABSTRACT

Background: With appropriate a
authors' goal was to apply machine
algorithm detects early alteration
affecting preload, afterload, and c

Perioperative Medicine

ORIGINAL CLINICAL RESEARCH REPORT

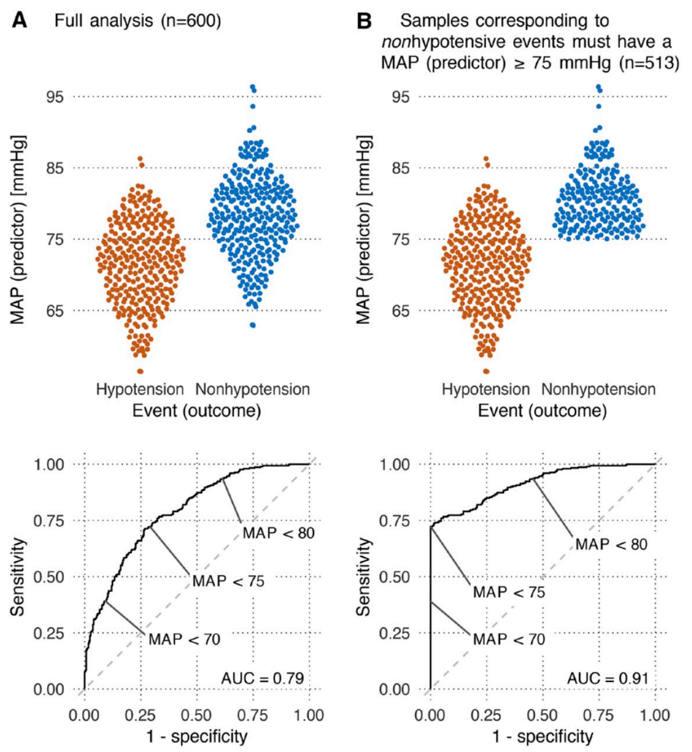
Ability of an Arterial Waveform Analysis–Derived Hypotension Prediction Index to Predict Future Hypotensive Events in Surgical Patients

Simon James Davies, MD,* Simon Tilma Vistisen, PhD,† Zhongping Jian, PhD,‡ Feras Hatib, PhD,‡ and Thomas W. L. Scheeren, MD, PhD§

BACKGROUND: Intraoperative hypotension is associated with worse perioperative outcomes for patients undergoing major noncardiac surgery. The Hypotension Prediction Index is a unitless number that is derived from an arterial pressure waveform trace, and as the number increases, the risk of hypotension occurring in the near future increases. We investigated the diagnostic ability of the Hypotension Prediction Index in predicting impending intraoperative hypotension in comparison to other commonly collected perioperative hemodynamic variables.
METHODS: This is a 2-center retrospective analysis of patients undergoing major surgery. Data were downloaded and analyzed from the Edwards Lifesciences EV1000 platform. Receiver operating characteristic curves were constructed for the Hypotension Prediction Index and other hemodynamic variables as well as event rates and time to event.

After some time there was a lot of criticism

"**Model Feature Selection and Training:** A hypotensive event was calculated by identifying a section of at least 1-min duration such that all data points in the section showed MAP < 65 mmHg. An event, or positive data point, was chosen as the sample recorded 5, 10, or 15 min before the hypotensive event. A nonhypotensive event was calculated by identifying a 30-min continuous section of data points such that the section was at least 20 min apart from any hypotensive event, and all data points in that section showed MAP > 75 mmHg. A nonevent, or negative data point, was the center point of the nonhypotensive event."



Enevoldsen, Anesthesiology, 2022

Faculty of Health

The scientific scandal of the decade? Researcher takes on med-tech giant

In recent years, associate professor Simon Tilma Vistisen has fought for his research integrity. In 2017-2018, he collaborated with researchers from the American medico-giant Edwards Lifesciences, but subsequently became aware of a fatal error. This marked the beginning of a long and tough battle.

Photo: Simon Fischel, AU Health. Generated by Adobe Firefly.

Unsupervised machine learning

Unsupervised machine learning

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Typical classification

JKU
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Alternative truth.....

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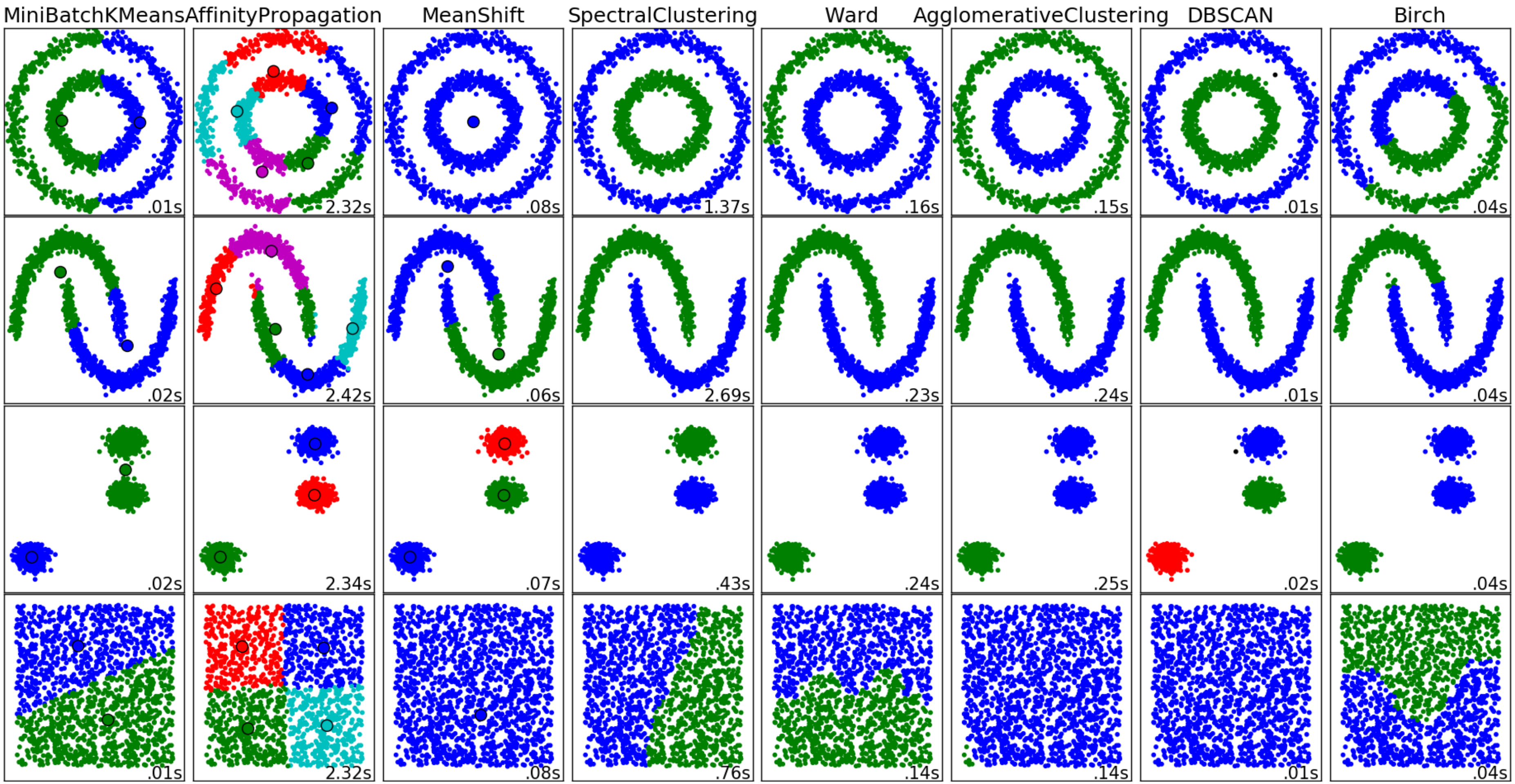
Several famous clustering algorithms



Identifying Distinct Subgroups of ICU Patients: A Machine Learning Approach

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Kelly C. Vranas, MD[1,2]; Jeffrey K. Jopling, MD, MSHS[1,3]; Timothy E. Sweeney, MD, PhD[4]; Meghan C. Ramsey, MD[1,5]; Arnold S. Milstein, MD, MPH[1]; Christopher G. Slatore, MD, MS[6,2]; Gabriel J. Escobar, MD[7]; Vincent X. Liu, MD, MS[7]

Description of the clusters

Patient Subgroup Characteristics	Cluster 1 ($n = 1,933$; 38.7%) Relatively Healthy, Short-Stay ICU Patients	Cluster 2 ($n = 622$; 12.4%) Older Patients Suffering Catastrophic Illness	Cluster 3 ($n = 1,250$; 25.0%) Postsurgical and Postprocedural Patients	Cluster 4 ($n = 897$; 17.9%) Older Patients Discharged With Long-Term Care Needs	Cluster 5 ($n = 207$; 4.1%) Prior Healthy Patients With Prolonged Stay and Good Recovery	Cluster 6 ($n = 91$; 1.8%) Patients With Severe Illness and Desire for Limits of Life-Sustaining Therapy
Patient						
Age (yr)	60.9 ± 17.1	72.7 ± 14.1	63.8 ± 15.0	74.8 ± 12.7	58.7 ± 16.3	79.4 ± 11.6
Male, %	54.6	52.1	60.0	47.5	54.1	53.9
Comorbidity (Comorbidity Point Score, version 2)	44 ± 46	65 ± 52	35 ± 35	63 ± 54	48 ± 49	70 ± 54
Hospitalization						
Emergency department admission, %	100.0	86.8	21.5	82.8	79.7	100.0
Most common diagnosis	Sepsis (19.8%)	Sepsis (38.9%)	**Acute myocardial infarction** (10.1%)	Sepsis (27.6%)	Sepsis (24.6%)	Sepsis (28.9%)
Need for procedure, %	0.2	9.7	**76.9**	17.2	19.8	4.4
Code status, %						
Do not resuscitate	0.0	18.0	0.0	28.2	0.0	0.0
Partial code	0.0	0.8	0.0	0.0	0.5	**100.0**
Predicted hospital mortality, %	4.8 ± 7.6	**16.5 ± 19.0**	1.9 ± 3.0	9.4 ± 11.9	8.1 ± 11.6	**22.5 ± 19.7**

Vranas, CCM, 2017

Archives of Cardiovascular Disease 117 (2024) 392–401

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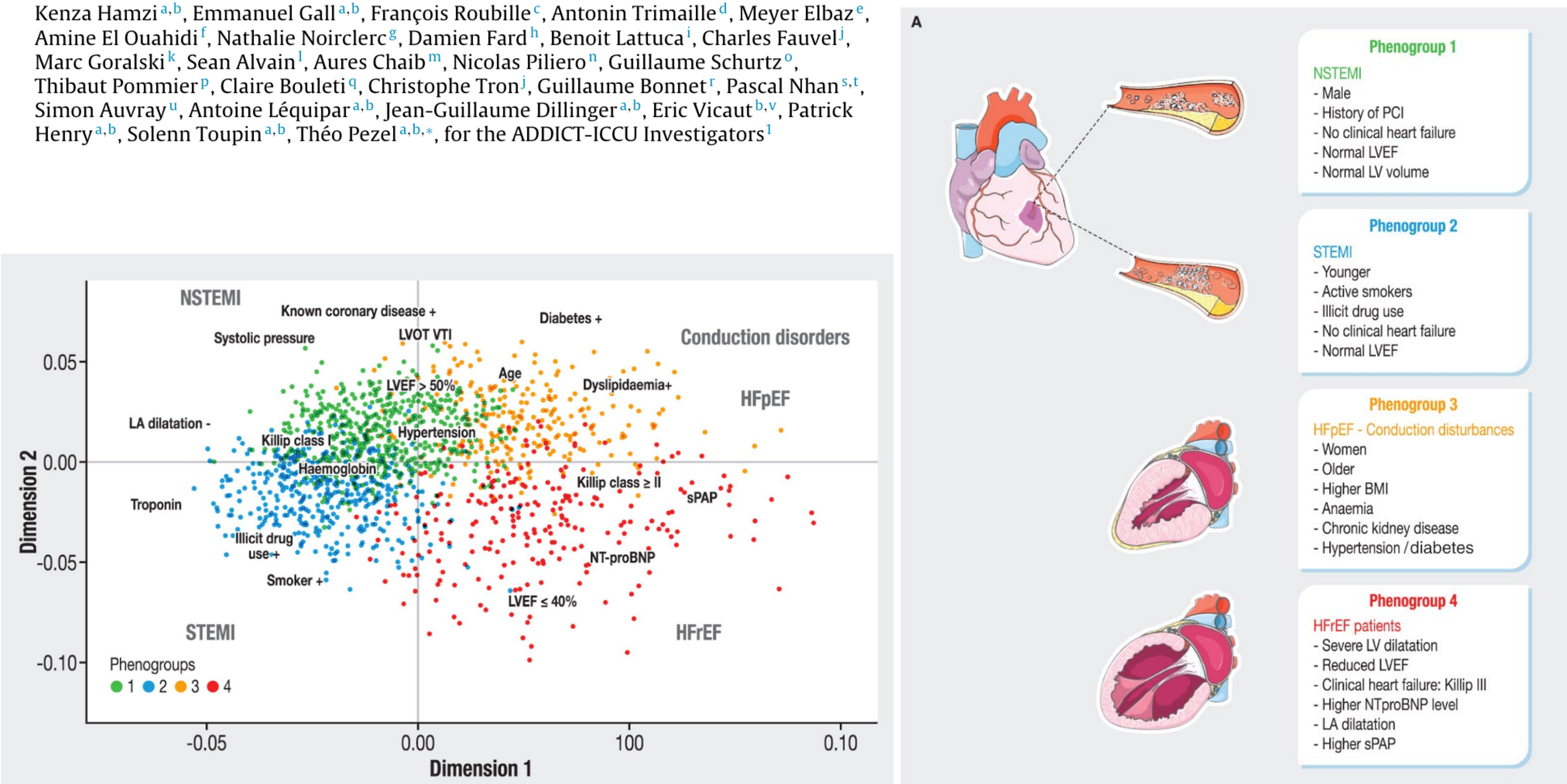
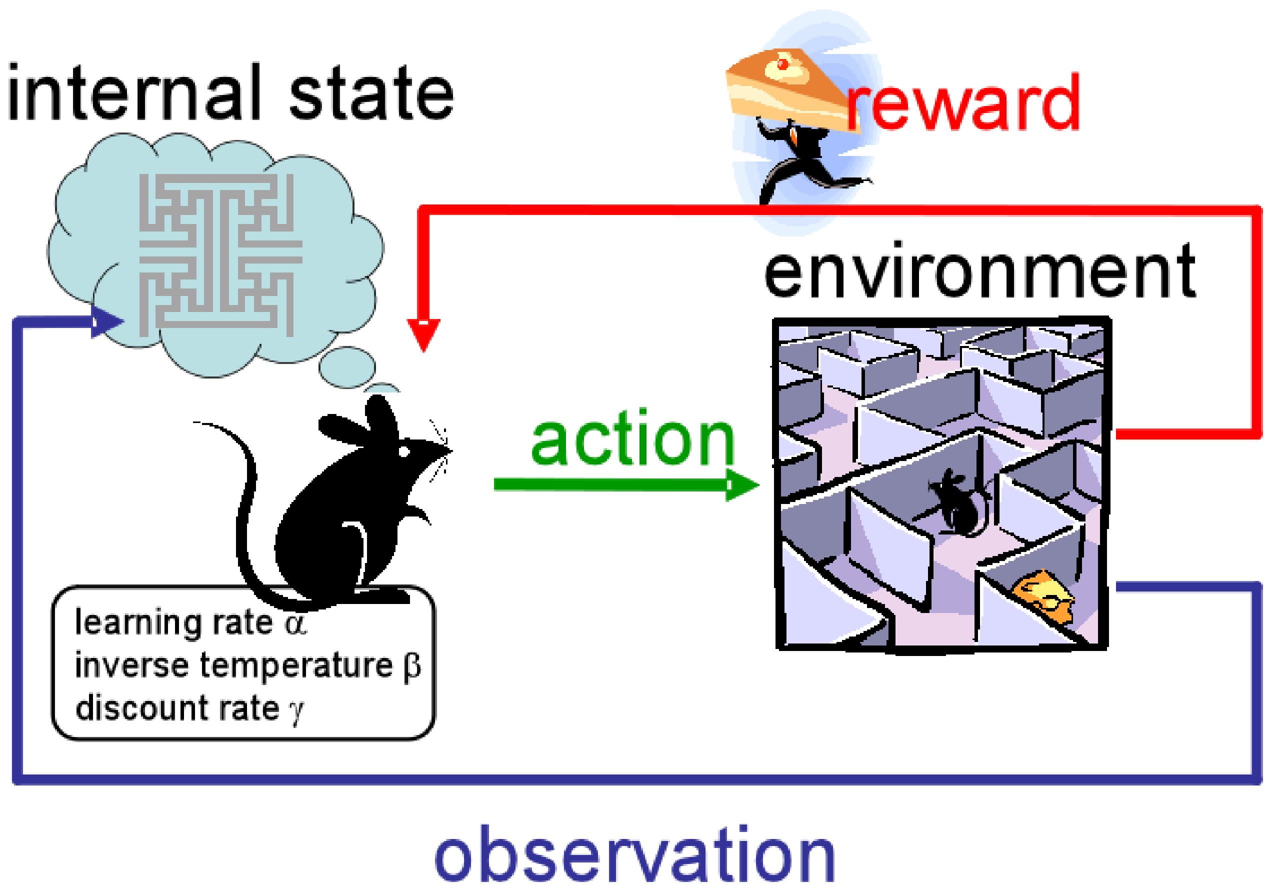
Clinical Research

Phenotypic clustering of patients hospitalized in intensive cardiac care units: Insights from the ADDICT-ICCU study

Kenza Hamzi[a,b], Emmanuel Gall[a,b], François Roubille[c], Antonin Trimaille[d], Meyer Elbaz[e], Amine El Ouahidi[f], Nathalie Noirclerc[g], Damien Fard[h], Benoit Lattuca[i], Charles Fauvel[j], Marc Goralski[k], Sean Alvain[l], Aures Chaib[m], Nicolas Piliero[n], Guillaume Schurtz[o], Thibaut Pommier[p], Claire Bouleti[q], Christophe Tron[j], Guillaume Bonnet[r], Pascal Nhan[s,t], Simon Auvray[u], Antoine Léquipar[a,b], Jean-Guillaume Dillinger[a,b], Eric Vicaut[b,v], Patrick Henry[a,b], Solenn Toupin[a,b], Théo Pezel[a,b,*], for the ADDICT-ICCU Investigators[1]



Reinforcement learning

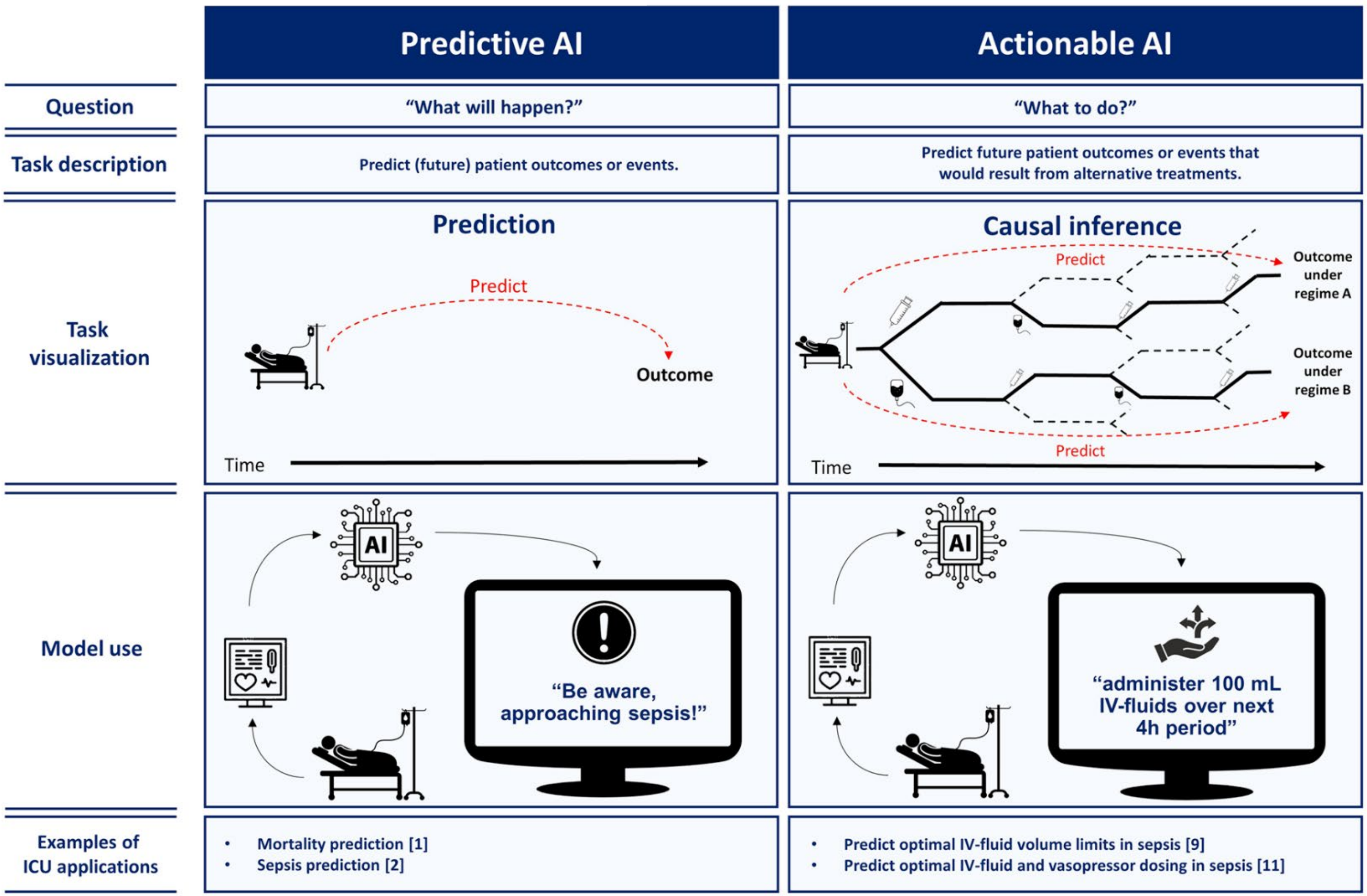


Intensive Care Med (2023) 49:1114–1116
https://doi.org/10.1007/s00134-023-07102-y

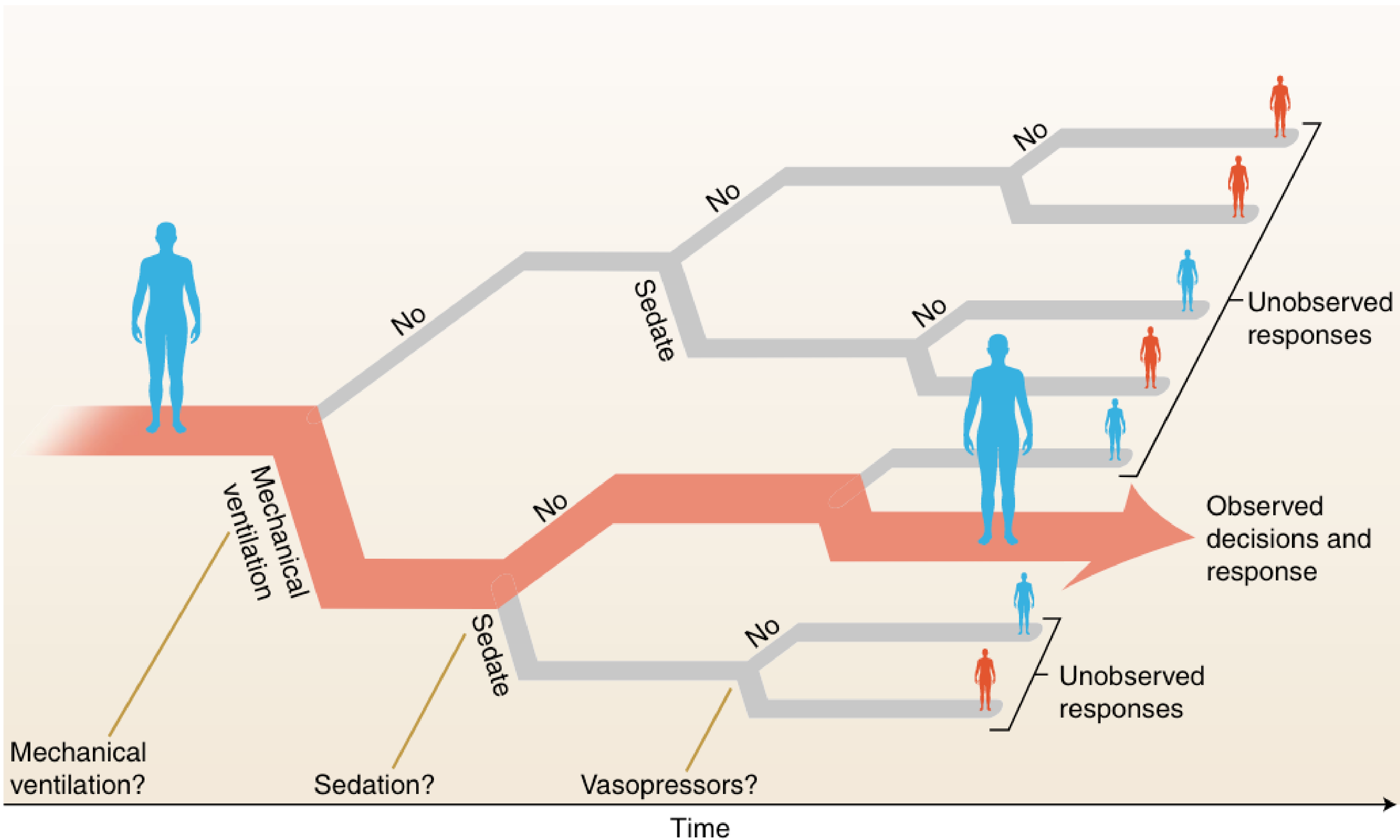
WHAT'S NEW IN INTENSIVE CARE

The future of artificial intelligence in intensive care: moving from predictive to actionable AI

Jim M. Smit[1,2*], Jesse H. Krijthe[2] and Jasper van Bommel[1] on behalf of the Causal Inference for ICU Collaborators



Reinforcement learning in healthcare



Gottesmann, Nature Medicine, 2019

nature medicine
ARTICLES
https://doi.org/10.1038/s41591-018-0213-5

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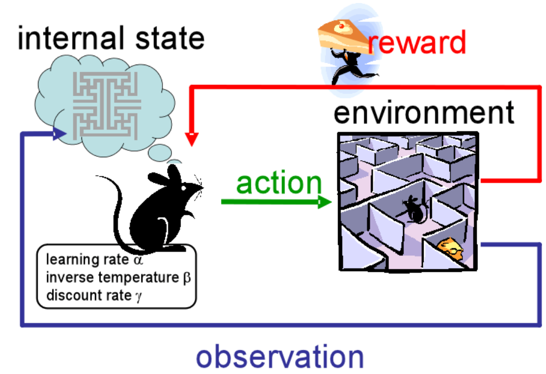
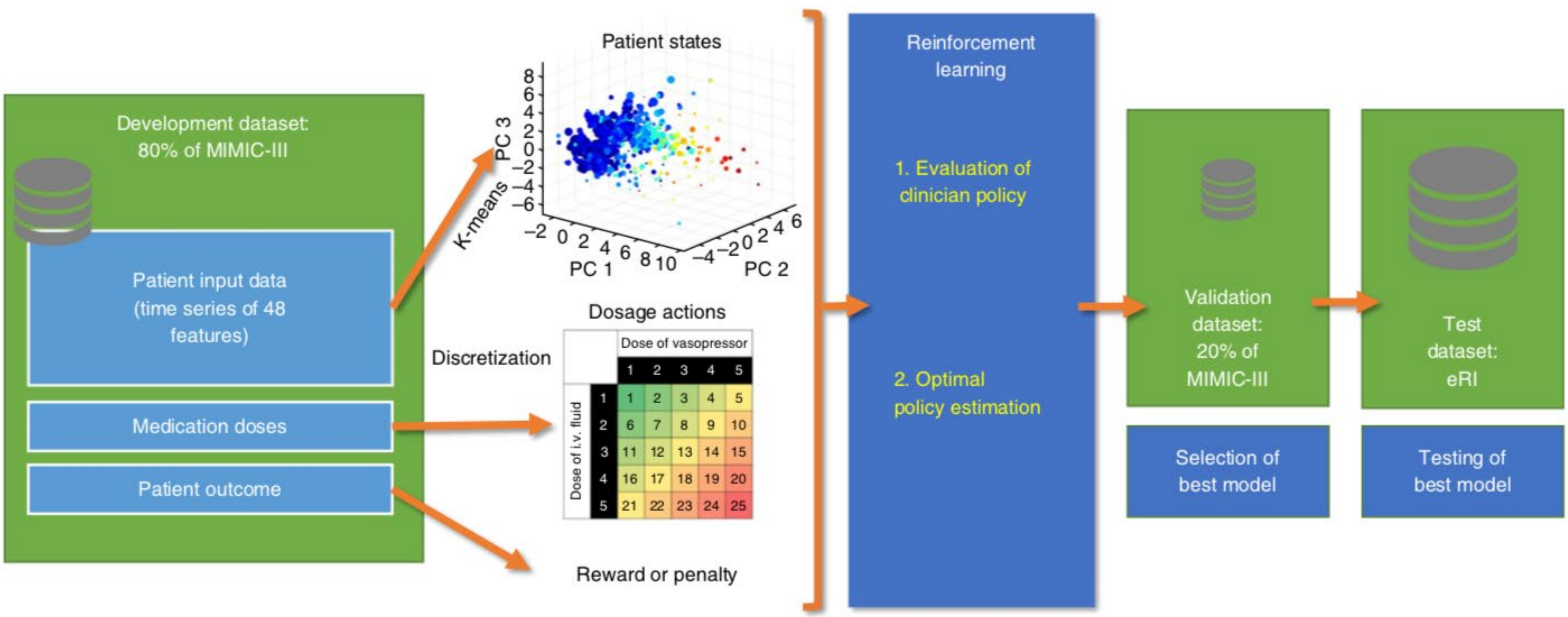
The Artificial Intelligence Clinician learns optimal treatment strategies for sepsis in intensive care

Matthieu Komorowski[1,2,3], Leo A. Celi[3,4], Omar Badawi[3,5,6], Anthony C. Gordon[1*] and A. Aldo Faisal[2,7,8,9*]





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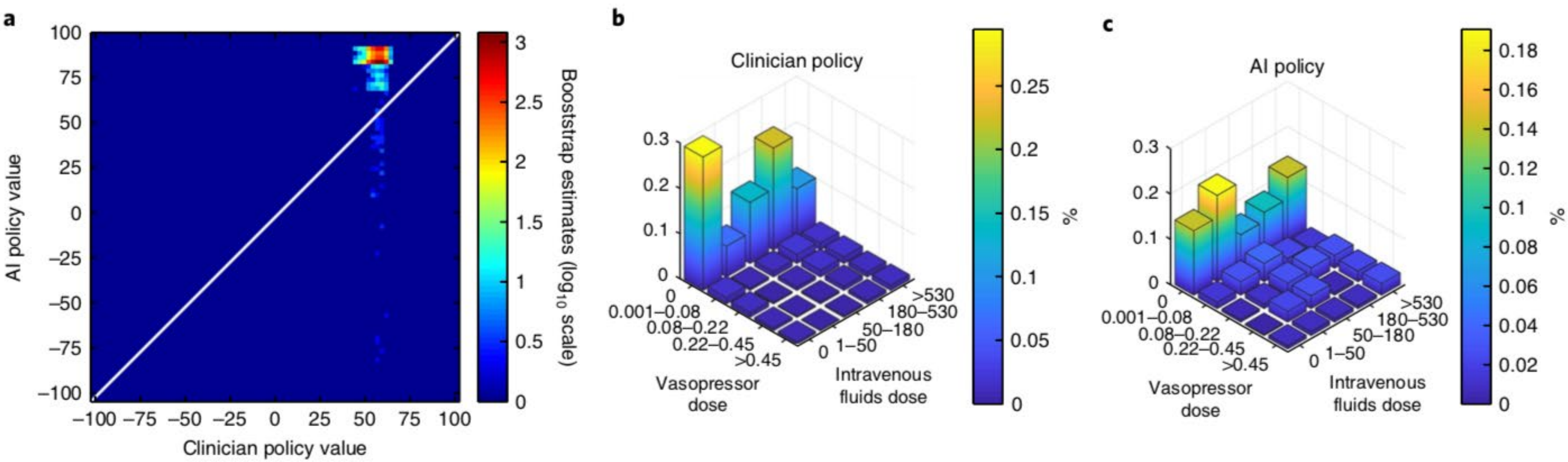


Cureus
Part of SPRINGER NATURE

Open Access Original Article

DOI: 10.7759/cureus.59662

Comparative Analysis of Artificial Intelligence (AI) Languages in Predicting Sequential Organ Failure Assessment (SOFA) Scores

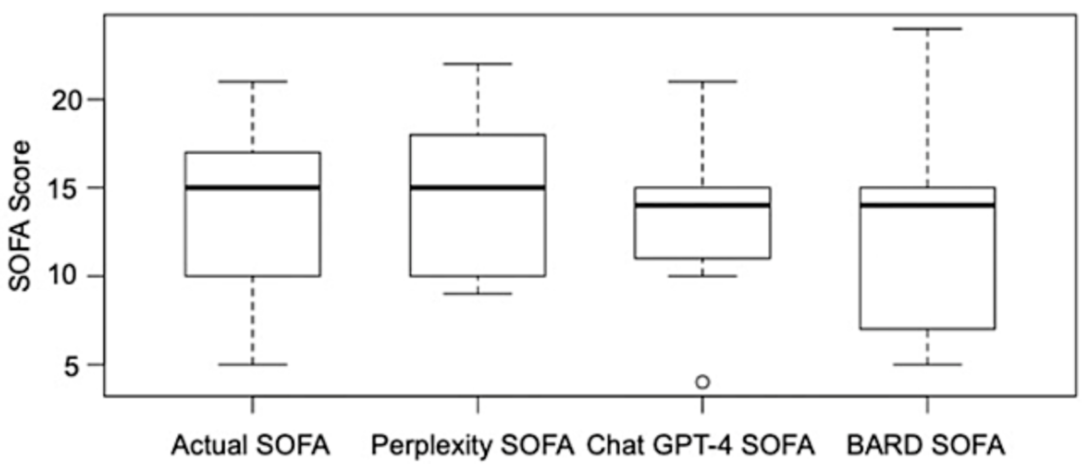
Review began 04/02/2024
Review ended 04/24/2024
Published 05/05/2024

Fuat H. Saner [1], Yasemin M. Saner [2], Ehab Abufarhaneh [1], Dieter C. Broering [1], Dimitri A. Raptis [1]

1. Organ Transplant Center of Excellence, King Faisal Specialist Hospital and Research Centre, Riyadh, SAU 2. Department of Urology, Medical Center University Duisburg-Essen, Essen, DEU

Corresponding author: Fuat H. Saner, fuat.saner@me.com

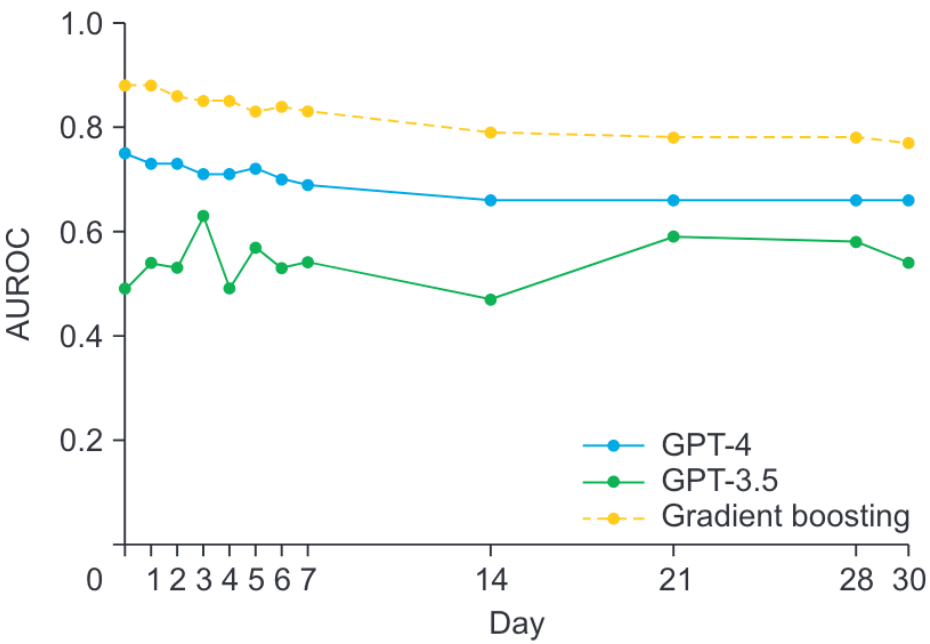
Patient 1	
Neurological	Open eyes to pain. Inappropriate words. Flexion to pain
Cardiovascular	MAP above 65 on norepinephrine 0.03 µg/kg/min. Lactate 5.3
Respiratory	Intubated. FiO_2=100%. paO2=75 mmHg
Renal	Creatinine: 2.5 mg/dl
Gastrointestinal	Bilirubin: 5 mg/dl
Hematology	Platelets: 99/nl

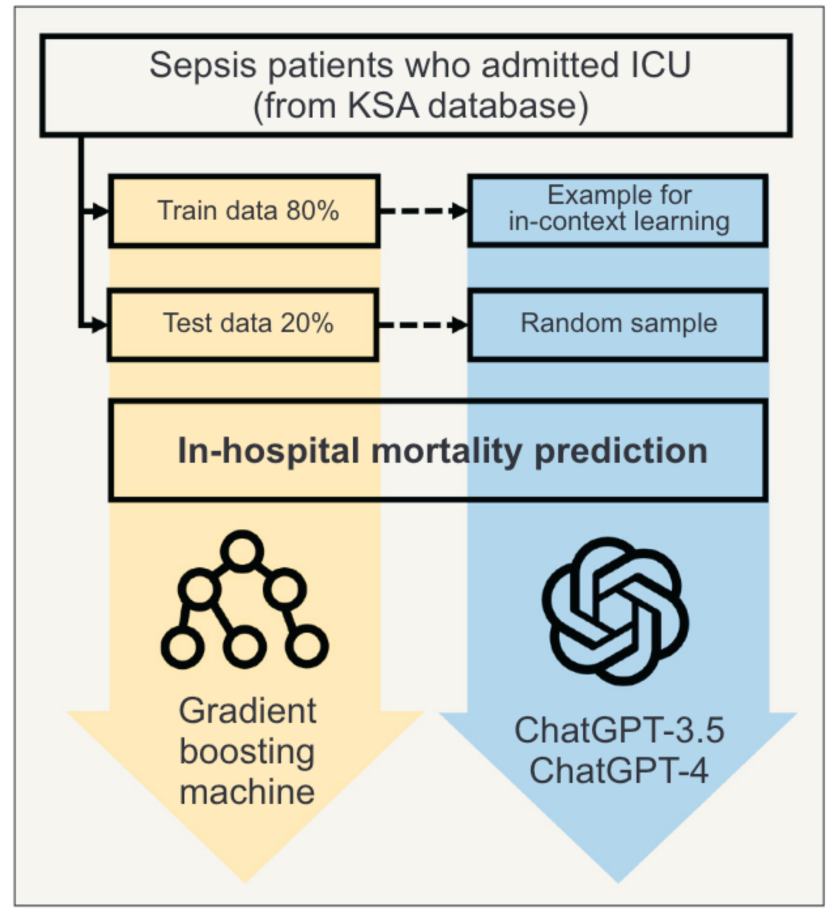


Original Article
Healthc Inform Res. 2024 July;30(3):266-276.
https://doi.org/10.4258/hir.2024.30.3.266
pISSN 2093-3681 • eISSN 2093-369X
HIR
Healthcare Informatics Research

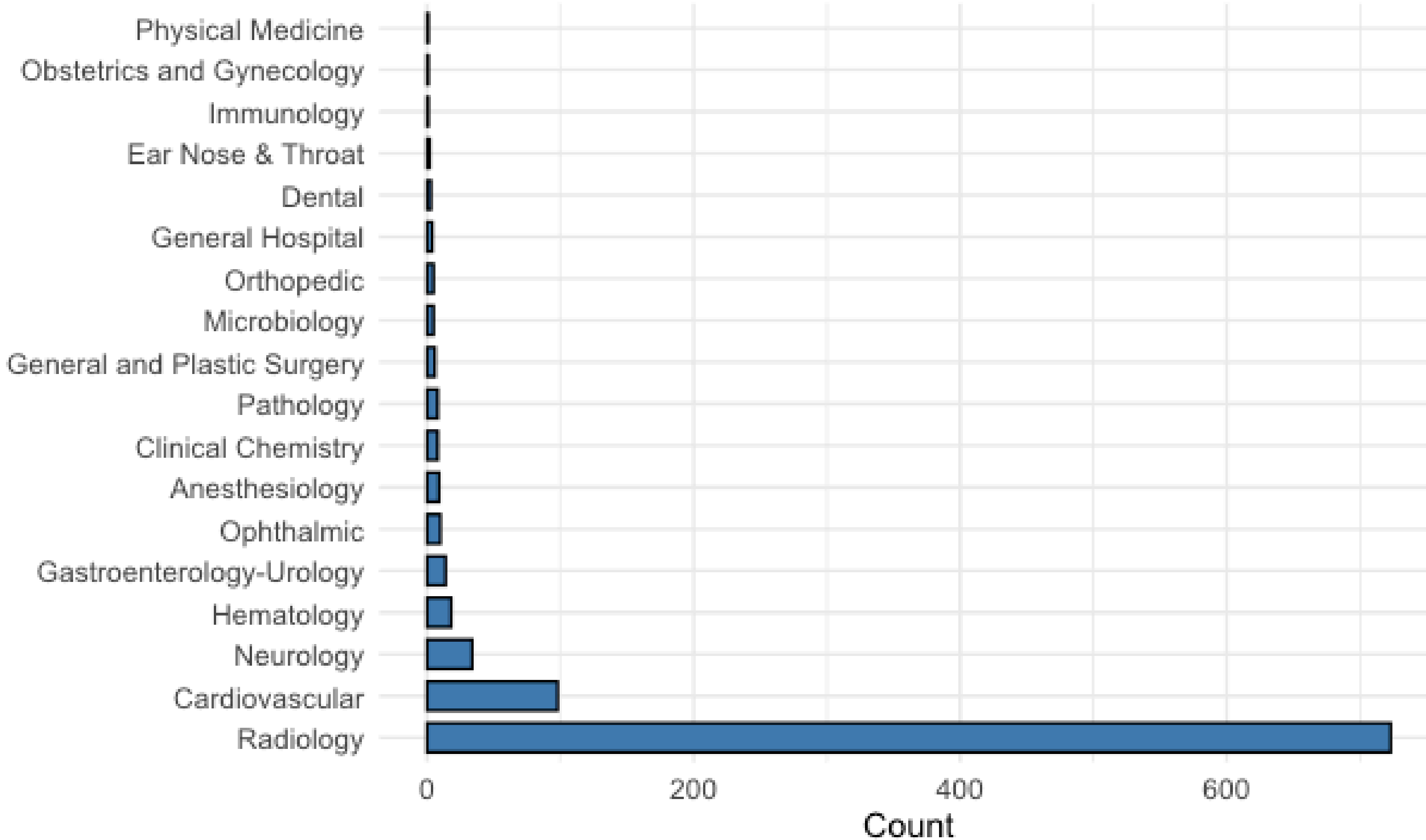
ChatGPT Predicts In-Hospital All-Cause Mortality for Sepsis: In-Context Learning with the Korean Sepsis Alliance Database

Namkee Oh[1,*], Won Chul Cha[2,*], Jun Hyuk Seo[3], Seong-Gyu Choi[1], Jong Man Kim[1], Chi Ryang Chung[4], Gee Young Suh[4,5], Su Yeon Lee[6], Dong Kyu Oh[6], Mi Hyeon Park[6], Chae-Man Lim[6], Ryoung-Eun Ko[4]
on behalf of the Korean Sepsis Alliance





FDA approved algorithms



https://www.fda.gov/medical-devices/software-medical-device-samd/artificial-intelligence-and-machine-learning-aiml-enabled-medical-devices

Will AI influence medicine?

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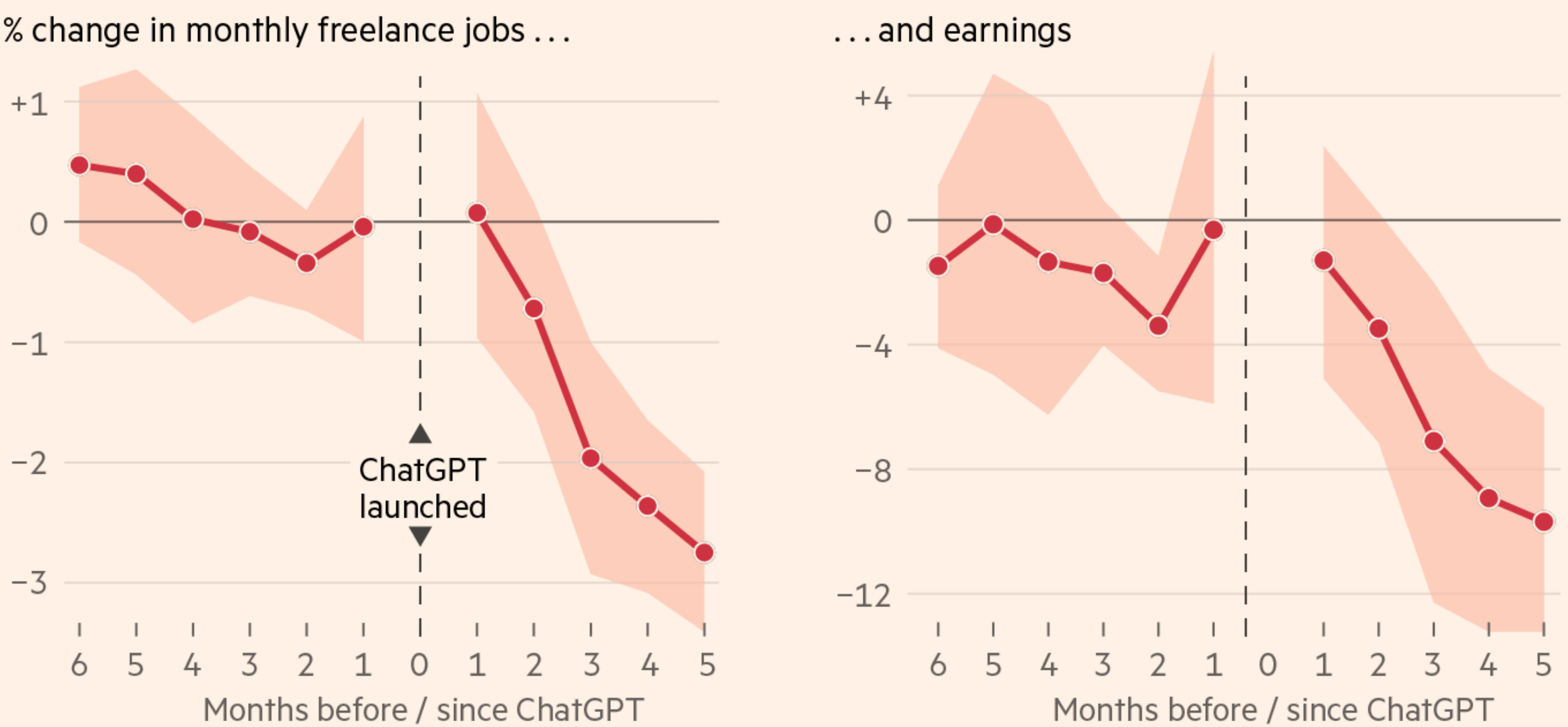
Generative AI is already taking white-collar jobs and wages in the online freelancing world

Change in employment and earnings from writing and editing jobs on an online freelancing platform after the launch of ChatGPT



Source: *The Short-Term Effects of Generative AI on Employment: Evidence from an Online Labor Market (Hui et al, 2023)*

Quintessence

- There are three ML techniques that are widely used:

  Supervised, unsupervised and reinforcement learning

- They help for classification, clustering, and therapy recommendation

- Proof of concept, but still far away from daily clinical usage