SAARSIU

23éme congrès national 14, 15, 16 Décembre 2023, Hôtel MERCURE Alger

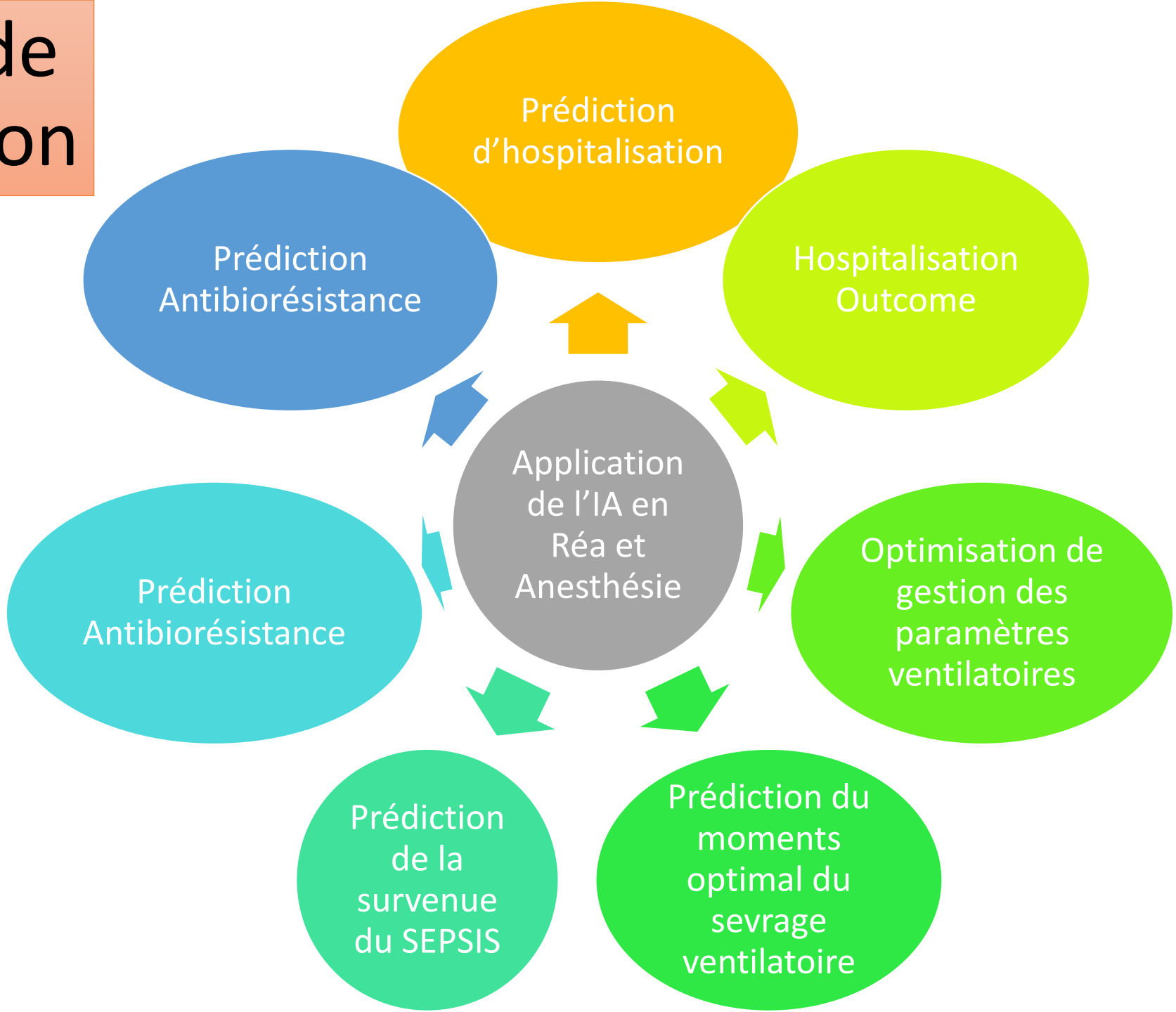
Intelligence artificielle en Réanimation et Anesthésie de quoi parle-t ’on ?

N.MEGHATRIA S.BOUDERRA

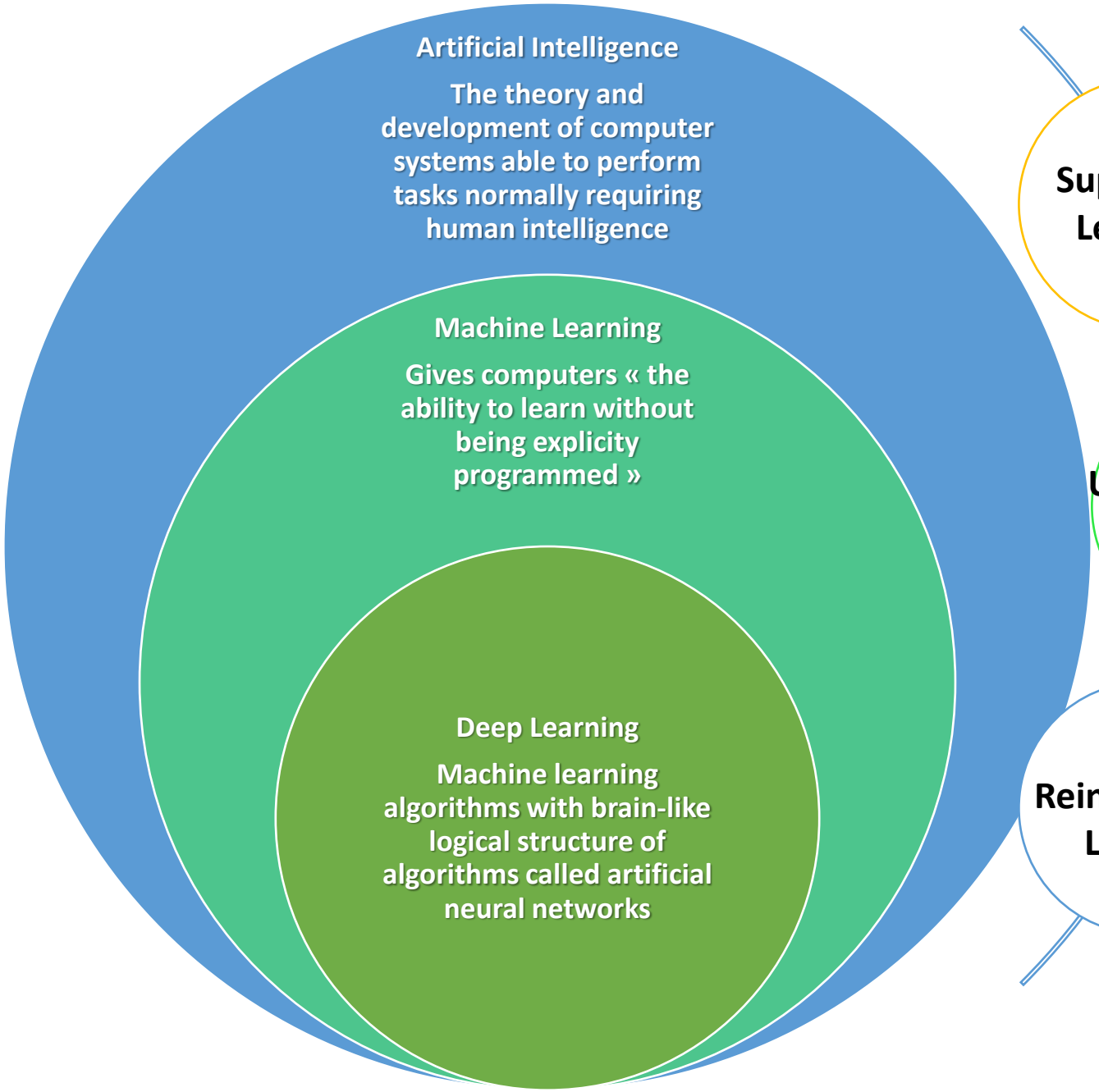
Service d’anesthésie réanimation - EHS CHERCHELL


Introduction

Intérêt de la question



Définition



Supervised Learning

Apprende la y=f(x)

régression et classification

Unssupervised Learning

Apprender la structure des donné

Clusterring

Reduction dimmentionnel

Reinforcement Learning

Apprendre

la stratégie optimal

Matériel et méthode

Revue de la littérature sur l'application de Intelligence Artificielle aux Urgences et en Réanimation Anesthésie jusqu'à 2023.

Résultat

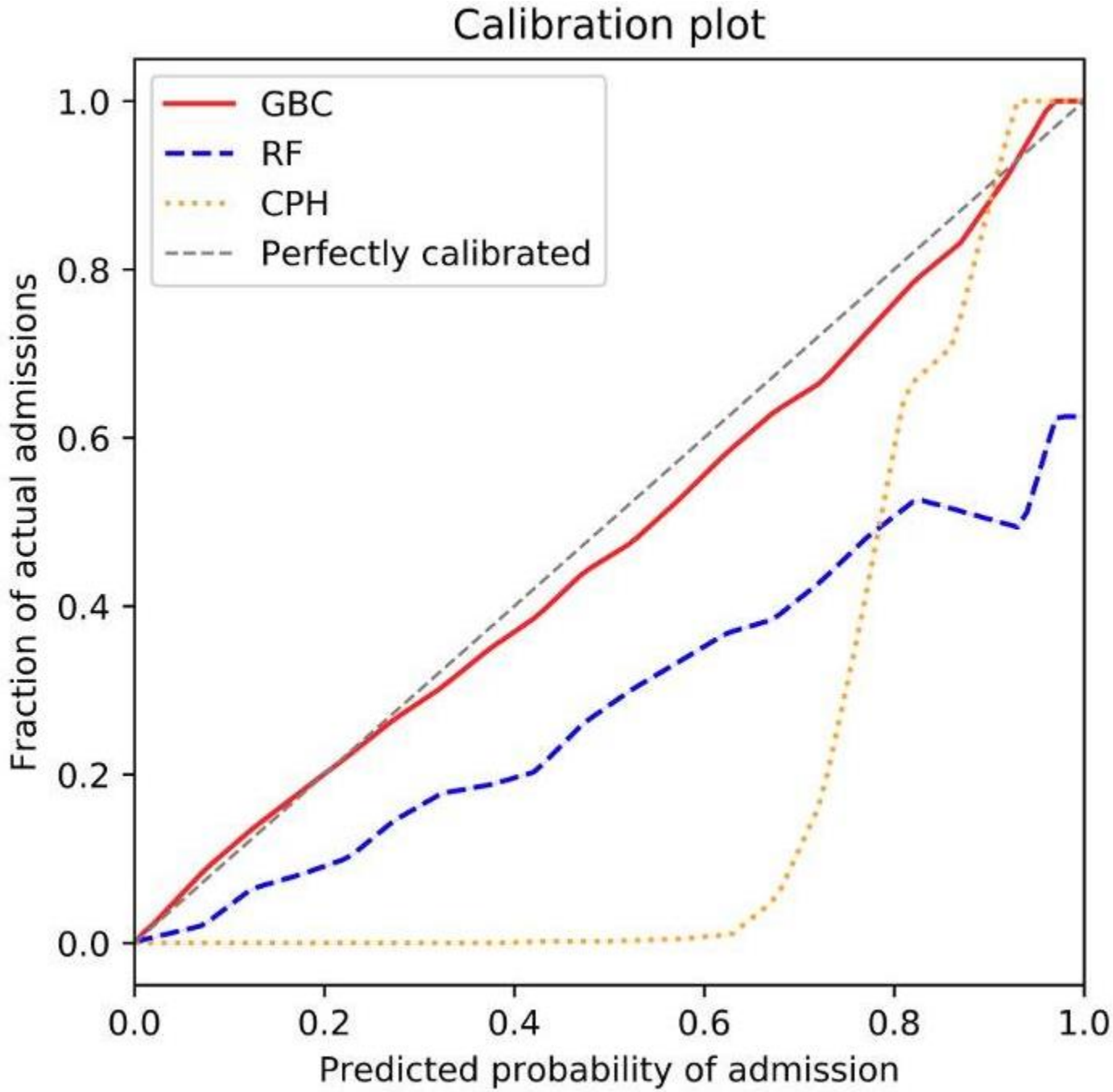
IA qui prédis l'hospitalisation a partir du des dossiers médicaux

RESEARCH ARTICLE

Predicting the risk of emergency admission with machine learning: Development and validation using linked electronic health records

Fatemeh Rahimian[1,2]*, Gholamreza Salimi-Khorshidi[1,2]*, Amir H. Payberah[1,2], Jenny Tran[1,2], Roberto Ayala Solares[1,2], Francesca Raimondi[1,2], Milad Nazarzadeh[1,2], Dexter Canoy[1,2], Kazem Rahimi[1,2,3]

1 Deep Medicine, Oxford Martin School, Oxford, United Kingdom, **2** The George Institute for Global Hea University of Oxford, Oxford, United Kingdom, **3** Oxford University Hospitals NHS Foundation Trust, Oxf United Kingdom



UK 2018

IA qui analyse les données manuscrite du médecin sur le dossier médicale

Scalable and accurate deep learning for electronic health records

Alvin Rajkomar*[1,2], Eyal Oren*[1], Kai Chen[1], Andrew M. Dai[1], Nissan Hajaj[1], Peter J. Liu[1], Xiaobing Liu[1], Mimi Sun[1], Patrik Sundberg[1], Hector Yee[1], Kun Zhang [1], Yi Zhang[1], Gavin E. Duggan[1], Gerardo Flores[1], Michaela Hardt[1], Jamie Irvine[1], Quoc Le[1], Kurt Litsch[1], Jake Marcus[1], Alexander Mossin[1], Justin Tansuwan[1], De Wang[1], James Wexler[1], Jimbo Wilson[1], Dana Ludwig[2], Samuel L. Volchenboum[4], Katherine Chou[1], Michael Pearson[1], Srinivasan Madabushi[1], Nigam H. Shah[3], Atul J. Butte[2], Michael Howell[1], Claire Cui[1], Greg Corrado[1], and Jeff Dean[1]

[1]Google Inc, Mountain View, California
[2]University of California, San Francisco, San Francisco, California
[3]Stanford University, Stanford, California
[4]University of Chicago Medicine, Chicago, Illinois

Équipe Google 2017 Californie

JAMA Network Open

Identification ACC en extra hospitalier par IA depuis les appels téléphonique

January 2021

RCT: Effect of Machine Learning (ML) Alert on Dispatcher Recognition of Out-of-Hospital Cardiac Arrest During Calls to Emergency Medical Services (EMS)

POPULATION

419 Men, 235 Women

EMS calls about adults with suspected cardiac arrest

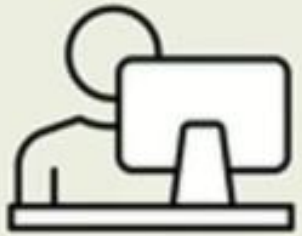
Mean, 70 y

SETTINGS / LOCATIONS

EMS in Copenhagen, Denmark

INTERVENTION

654 Calls randomized and analyzed



336 Protocol with ML alert suppressed
ML algorithm suspects cardiac arrest but does not warn dispatchers during the emergency call

318 Protocol with ML alert shown
ML algorithm suspects a cardiac arrest and displays an alert on dispatcher's monitor during the emergency call

PRIMARY OUTCOME

Rate of dispatcher recognition of subsequently confirmed out-of-hospital cardiac arrest

FINDINGS

There was no difference between EMS dispatcher recognition of out-of-hospital cardiac arrest among the group of dispatchers who receive the ML-generated alert and the group that did not receive the alert.

Numbers of dispatchers who recognized out-of-hospital arrest
Control group with ML alert suppressed: 304 of 336 cases
Intervention group with ML alert shown: 296 of 318 cases

Blomberg SN, Christensen HC, Lippert F, et al. Effect of machine learning on dispatcher recognition of out-of-hospital cardiac arrest during calls to emergency medical services: a randomized clinical trial. *JAMA Netw Open*. 2021;4(1):e2032320. doi:10.1001/jamanetworkopen.2020.32320

Optimisation dynamique des paramètres ventilatoire par un algorithme

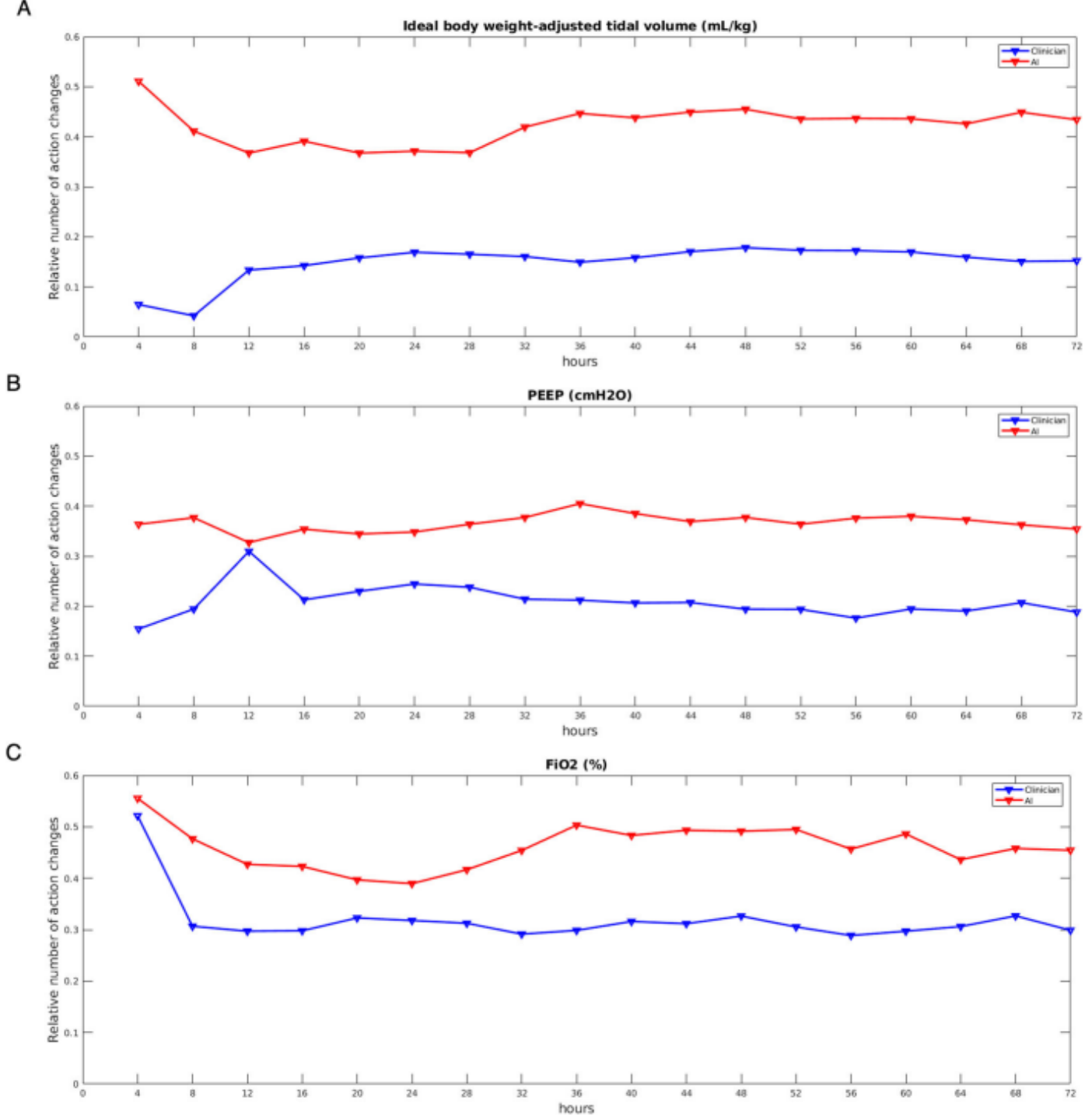
npj | Digital Medicine

ARTICLE OPEN

Development and validation of a reinf
algorithm to dynamically optimize mec
critical care

Arne Peine[1,10], Ahmed Hallawa[1,2,10], Johannes Bickenbach[1], Guido Dartmann[3], Le
Gerd Ascheid[2], Christoph Thiemermann[5], Andreas Schuppert[6], Ryan Kindle[7,8], Le

2021 Korée du Sud



Training (60%) / Validation (20%)

Testing 20%

Independent Testing

Moment optimal pour le sevrage ventilatoire prédis par l'IA

TABLE 4 The results of clinical evaluation and comparison.

Optimal Timing Prediction for Weaning MV

try weaning

Station	Bed	Patient ID	Name	Start Use	Hours	8hr	12hr	24hr	36hr	48hr	60hr	72hr	84hr	96hr	108hr	120hr
3BI				2021-05-23 21:03	63			36.88%	43.4%	23.43%	31.3%	56.35%				
3CI				2021-05-24 14:51	45	5.96%	11.23%	16.41%	22.52%	25.38%						
4BI				2021-05-25 02:20	33			46.77%	57.4%							
5CI				2021-05-23 19:00	65			12.69%	13.46%	15.15%	38.63%	35.12%				
5CI				2021-05-22 20:05	88					17.25%	16.88%	21.64%	23.1%	26.9%		
5CI				2021-05-21 15:25	116	10.64%		10.14%	6.9%	10.15%	2.69%	11.27%	7.92%	8.77%	7.07%	8.61%

weaning MV

Station	Bed	Patient ID	Name	Start Use	Hours	1 Day	2 Days	3 Days	4 Days	5 Days	6 Days	7 Days	8 Days	9 Days	10 Days	11 Days
3BI				2021-05-24 08:55	51	47.92%	43.73%	33.36%								
3BI				2021-05-25 09:15	26	56.69%	56.57%									
3BI				2021-05-24 09:35	50	20.99%	57.54%	72.48%								
3BI				2021-05-19 09:40	170	50.64%	59.64%	30.3%	28.96%	36.45%	28%	44.27%	31.19%			
3BI				2021-05-26 11:20	0	64.95%										
3BI				2021-05-22 09:05	99	34.62%	41.61%	50.98%	38.43%	21.2%						
3CI				2021-05-25 08:50	27	14.05%	46.71%									
4BI				2021-05-24 09:12	50	36.89%	43.39%	52.15%								
5CI				2021-05-24 08:50	51	33.53%	51.81%	66.49%								
6BI				2021-05-21 10:00	122	13.41%	23.95%	28.19%	34.2%	28.22%	30.43%					

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

ATLANTA USA
2019

Shamim Nemati, PhD,[1,*] Andre Holder, MD, MSc,[2] Fereshteh Razmi,[1] Matthew D. Stanley, MD,[3] Gari D. Clifford, PhD,[1,4]
and Timothy G. Buchman, PhD, MD[3,4]

Prédiction de survenue du SEPSIS en quelque heurs avant grâce au monitorage du patient par l'IA

Prédiction du profile antibiorésistance a partir de séquençage génétique par PCR grâce à 4 modèles IA

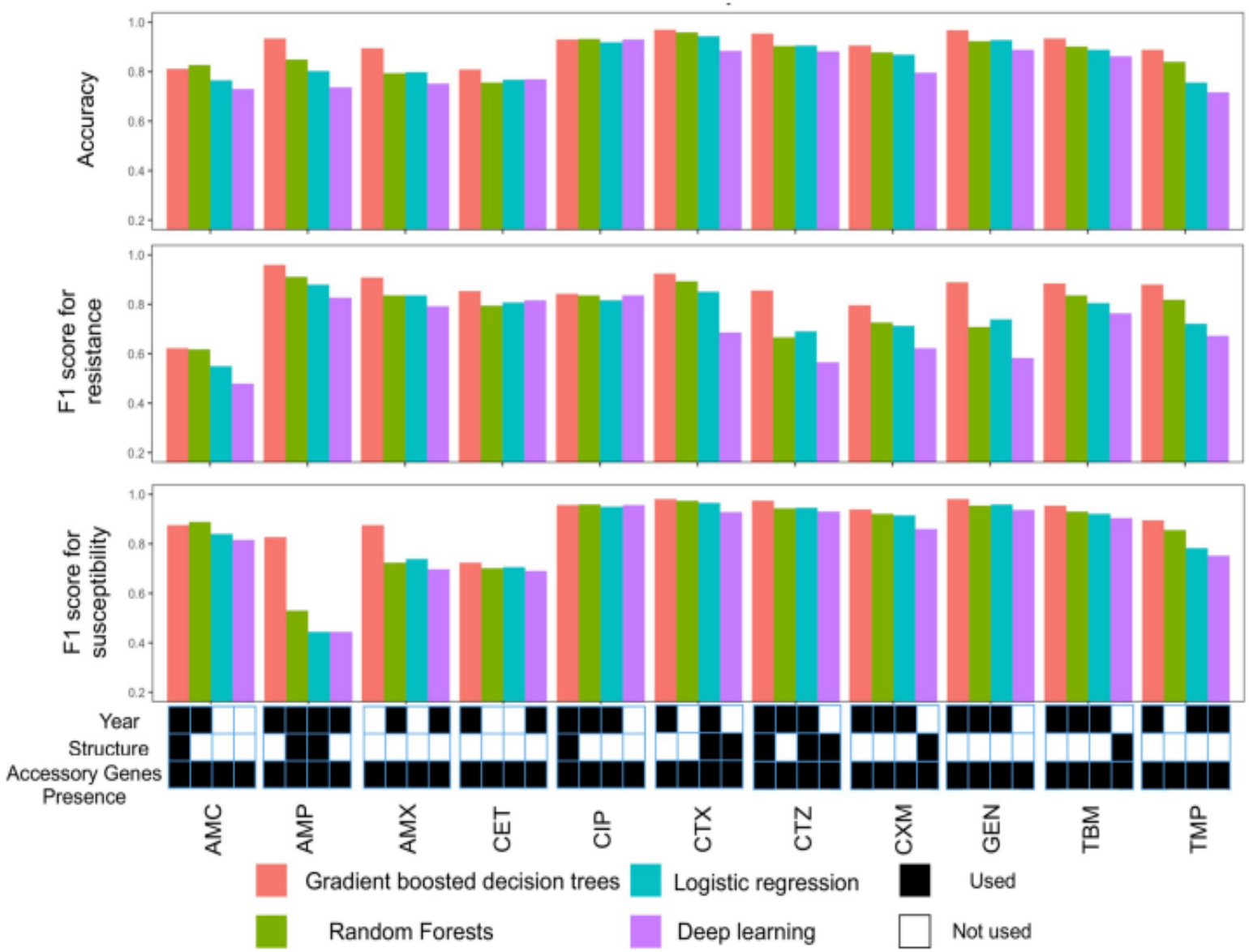


Fig 1. Prediction performance of the best tuned models. Accuracy and F1 score (harmonic mean of precision and recall; y-axis) for resistant (top panel) and susceptible (middle panel) phenotypes for four predictive models (red: gradient boosted decision trees; green: logistic regression; teal: random forests; purple: deep learning) across eleven antibiotics (x-axis). The best model of each class for every drug (x-axis) was identified based on the accuracy for predicting resistance and employed a number of possible combinations of gene presence, population structure, and year of isolation (lower panel; black: feature used; white: feature not used).

RESEARCH ARTICLE

Prediction of antibiotic resistance in *Escherichia coli* from large-scale pan-genome data

Danesh Moradigaravand[1,2]*, Martin Palm[3,4], Anne Farewell[3,4], Ville Mustonen[5,6], Jonas Warringer[3,4], Leopold Parts[1,7]*

1 Wellcome Sanger Institute, Wellcome Genome Campus, Hinxton, Cambridgeshire, United Kingdom, **2** Center for Computational Biology, Institute of Cancer and Genomic Sciences, University of Birmingham, Birmingham, United Kingdom, **3** Department for Chemistry and Molecular Biology, University of Gothenburg, Gothenburg, Sweden, **4** Centre for Antibiotic Resistance Research at the University of Gothenburg, Gothenburg, Sweden, **5** Organismal and Evolutionary Biology Research Programme, Department of Computer Science, Institute of Biotechnology, University of Helsinki, Helsinki, Finland, **6** Helsinki Institute for Information Technology HIIT, Helsinki, Finland, **7** Department of Computer Science, University of Tartu, Tartu, Estonia

Sydney 2018

Article | Published: 25 May 2023

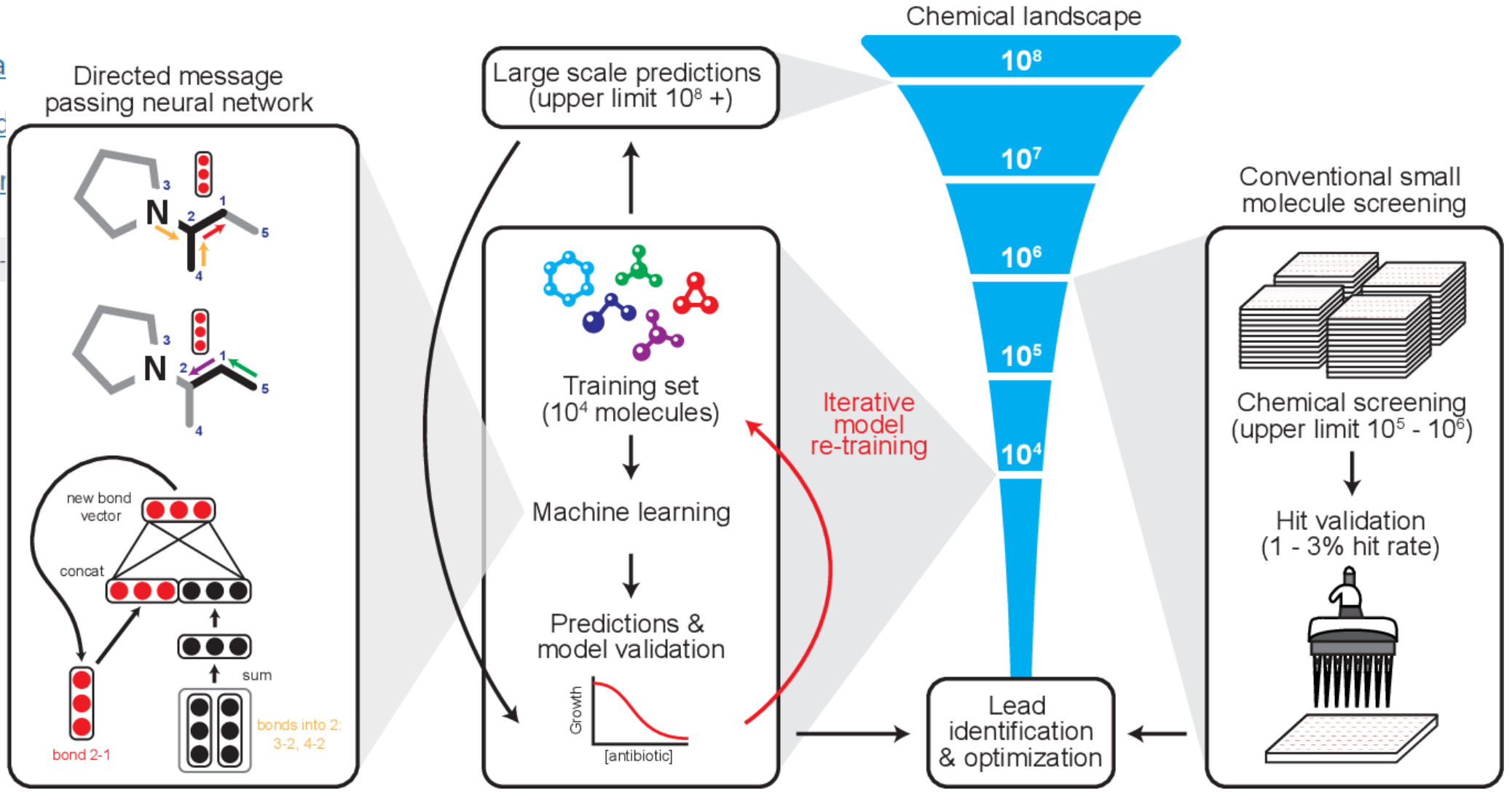
Deep learning-guided discovery of an antibiotic targeting *Acinetobacter baumannii*

Gary Liu, Denise B. Ca

Chiappino-Pepe, Saad

Brian K. Coombes, Tor

DOI: 10.1038/s41589-023-

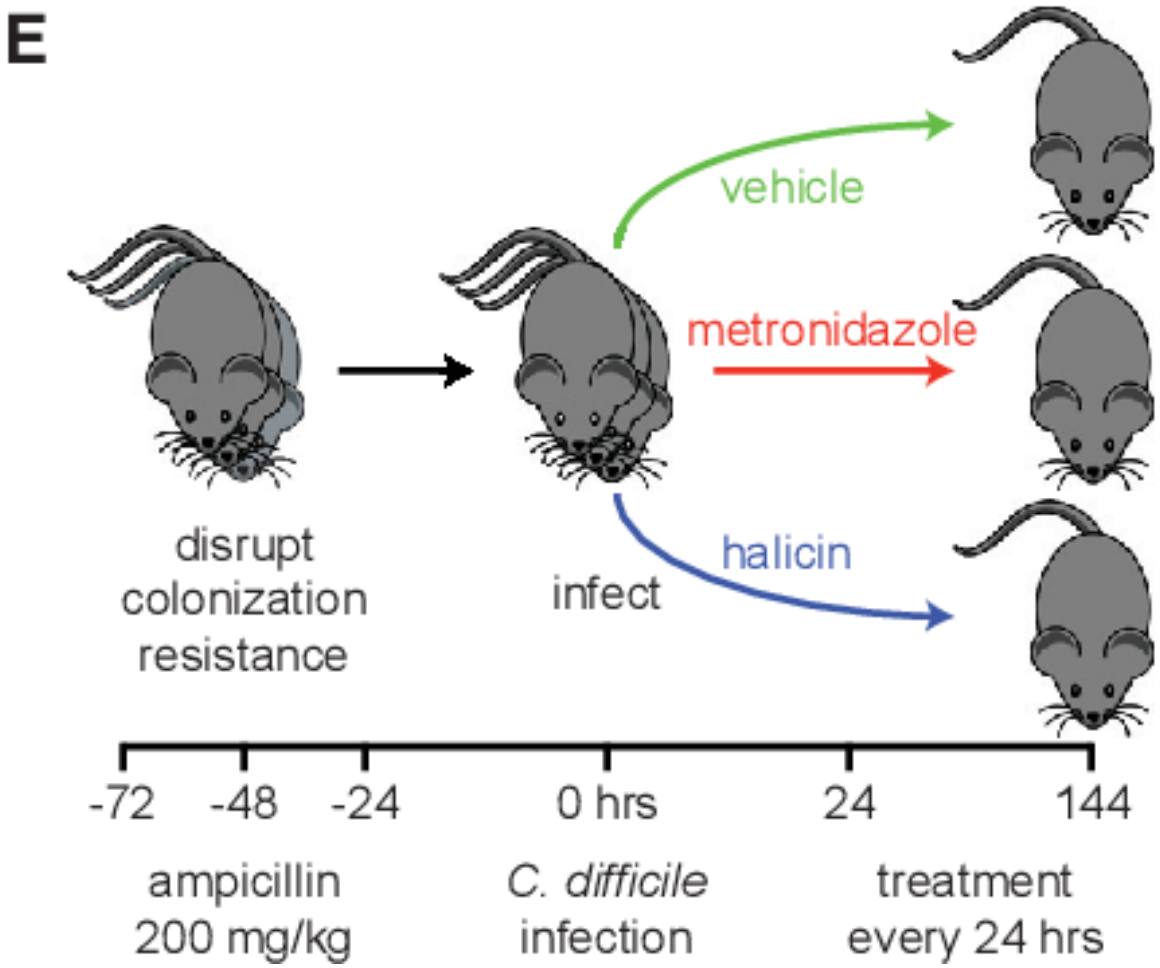


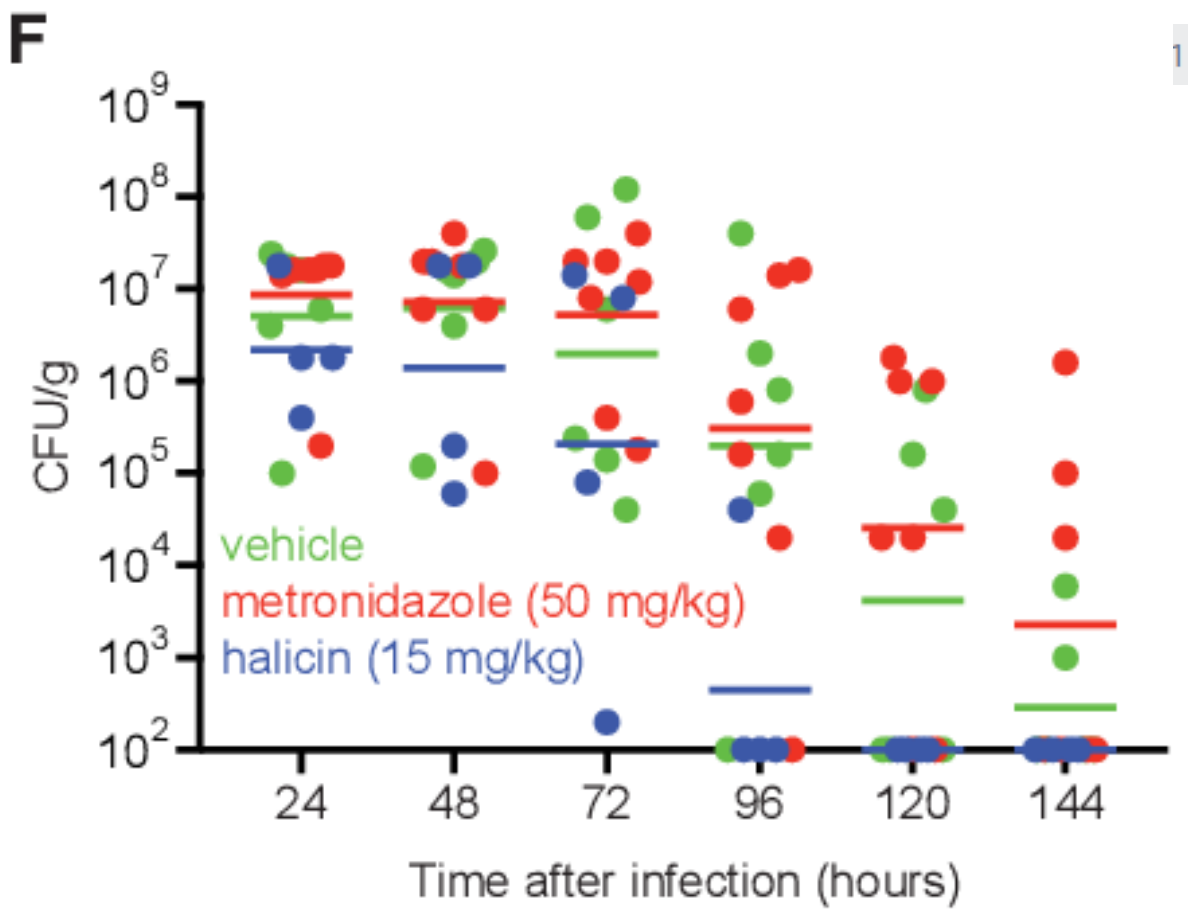
Halicine

Article | Published: 25 May 2023

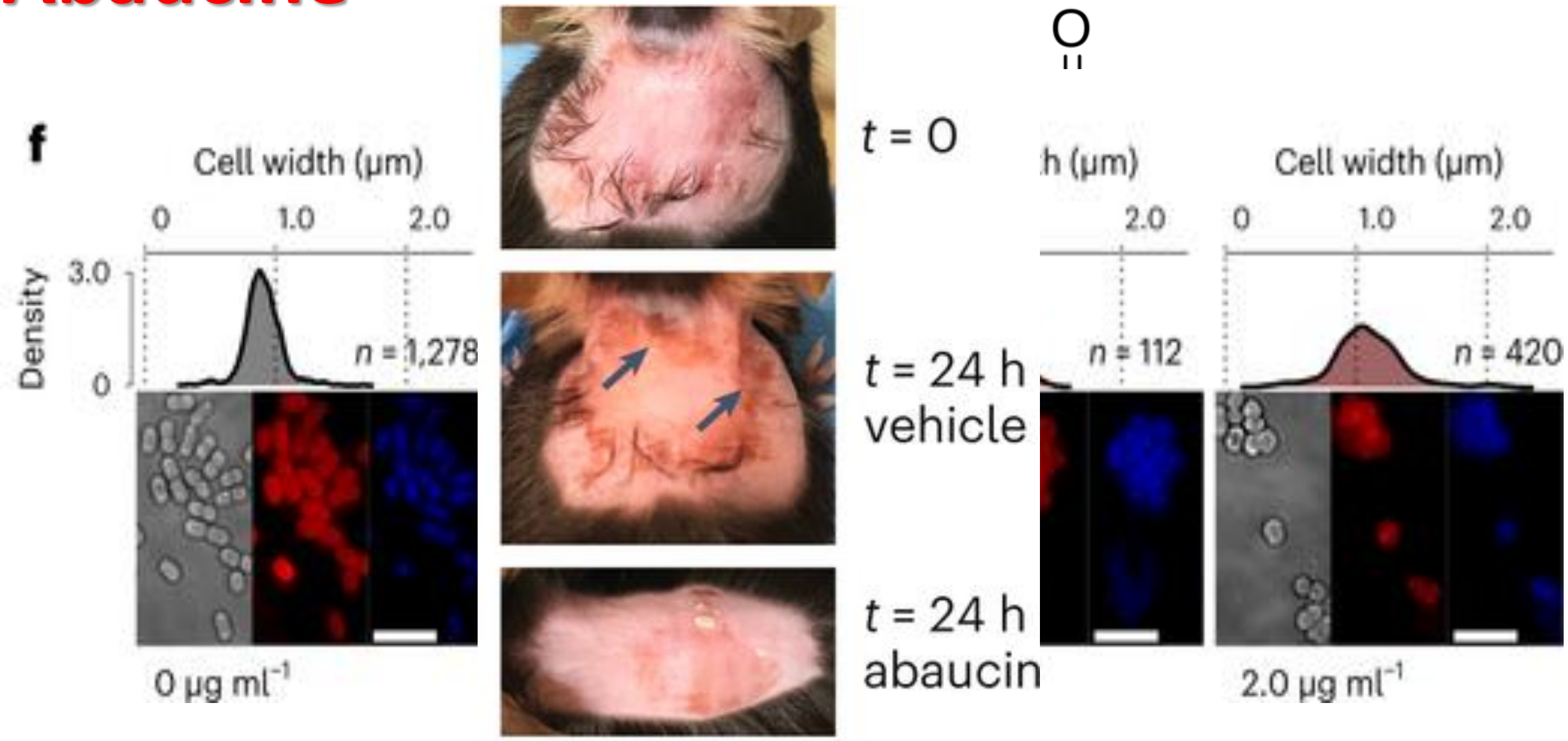
Deep learning-guided discovery of an antibiotic targeting *Acinetobacter baumannii*

Gary Liu, Denise B. Catacutan, Khushi Rathod, Kyle Swanson, Wengong Jin, Jody C. Mohammed, Anush Chiappino-Pepe, Saad A. Syed, Meghan Fragis, Kenneth Rachwalski, Jakob Magolan, Michael G. Surette, Brian K. Coombes, Tommi Jaakkola, Regina Barzilay, James J. Collins & Jonathan M. Stokes





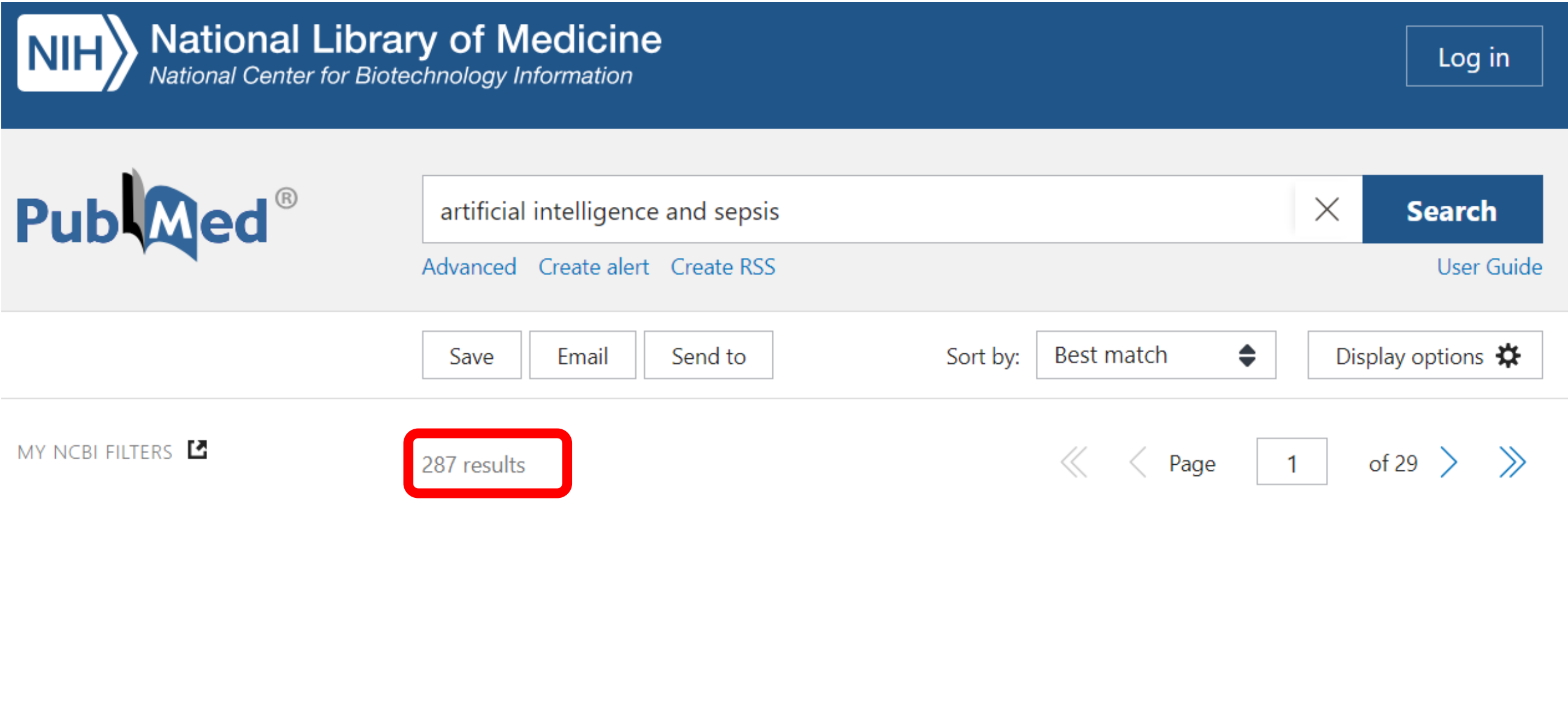
Abaucine


f
Cell width (μm)
0
1.0
2.0
Density
3.0
0
n = 1,278
0 μg ml⁻¹
t = 0
t = 24 h
vehicle
t = 24 h
abaucin
h (μm)
2.0
n = 112
Cell width (μm)
0
1.0
2.0
n = 420
2.0 μg ml⁻¹


Discussions

106 STARTUPS TRANSFORMING HEALTHCARE WITH AI

Où est donc cette IA ?



Alerte au AKJ, l'incident aux USA 2021

For numbered affiliations see end of the article.

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Research

Electronic health record a randomized clinical trial

BMJ 2021 ; 372 doi: https://doi.o
Cite this as: *BMJ* 2021;372:m4786

Opinion
The challenge of minimal risk in e

Article | Related content

F Perry Wilson, *associate professor*
Caitlin Partridge, data scientist[3], *Erica M*
Aditya Biswas, data scientist[1 2], *Harold*
Jason H Greenberg, assistant professor[2]
Fan Li, assistant professor[9], *Haiqun Lin,*
Dennis G Moledina, assistant professor[1]
Michael Simonov, instructor[2], *Jeffrey T*
Ugochukwu Ugwuowo, postdoctoral researcher[1 2]

BestPractice Advisory - [redacted]

Patient Safety (Advisory: 1)

AKI Alert:

Your patient has been identified as having acute kidney injury. Relevant creatinine values over the last seven days are listed below:

Most recent: 0.93 mg/dl

Lowest in past 7 days: 0.5 mg/dl

Highest in past 7 days: 0.93 mg/dl

THIS ALERT DOES NOT FIRE FOR ALL PATIENTS. This patient is part of a randomized trial. For more information click here: www.akistudy.org. For AKI best practices, click here: www.akistudy.org/aki-best-practices.

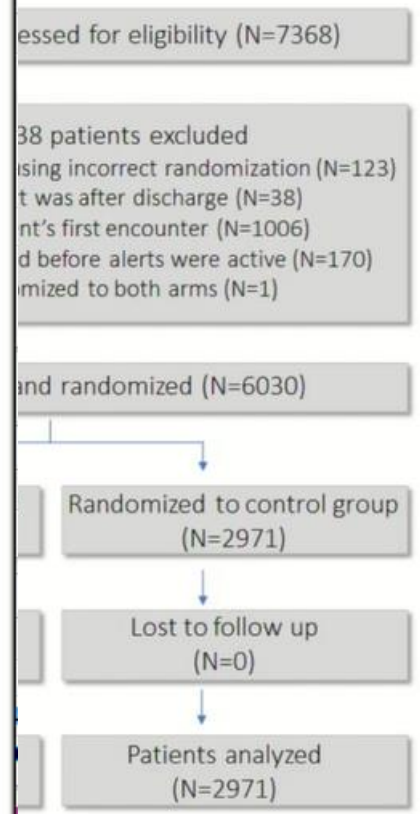
Open Order Set | Do Not Open — AKI ORDER SET preview

Add Problem | Do Not Add — Acute kidney injury › Edit details (Hospital problem, Share with patient)

Acknowledge Reason

Agree - Do not alert me for 48 hours | Disagree with alert because...

Accept | Dismiss



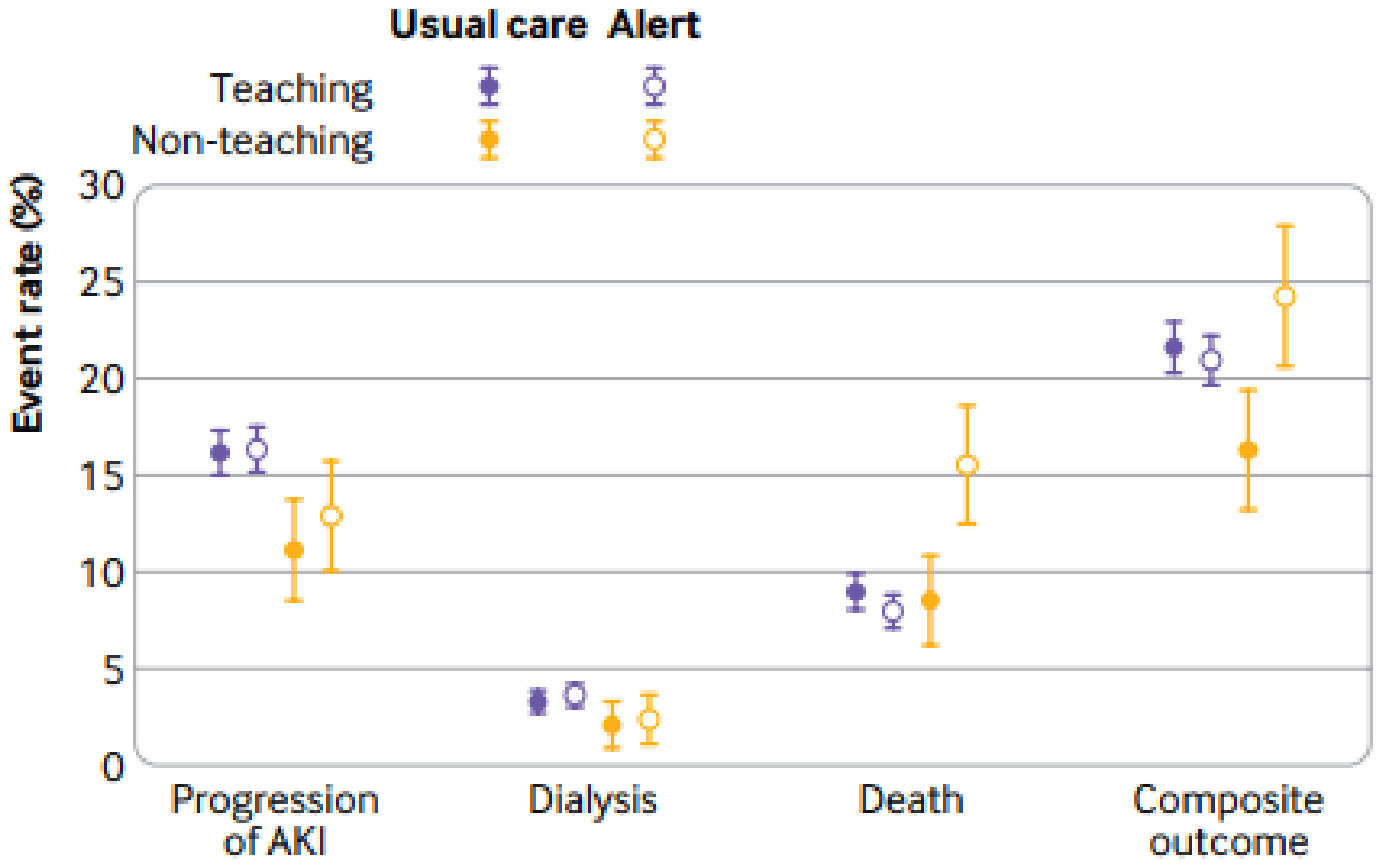


Fig 2 | Primary and secondary outcome events, stratified by hospital type. Error bars are 95% confidence intervals of the observed proportion of events. AKI=acute kidney injury

- Higher risk of death at 14 days in non-teaching hospitals with alerts (15.6% vs 8.6%, p=0.003)
- "We are left without a satisfying unifying explanation for the potential harm."

Conclusion

COPILOT

L'intelligence artificielle (IA) est un outil précieux en réanimation, mais elle ne remplace pas le médecin. Elle offre des capacités d'analyse de données à grande échelle, permettant d'identifier des tendances et des modèles qui pourraient échapper à l'œil humain. Par exemple, l'IA peut aider à surveiller les signes vitaux des patients, à prédire les risques de complications et à personnaliser les plans de traitement. Cependant, la décision finale revient toujours au médecin. L'IA est un outil d'aide à la décision, elle fournit des informations précieuses qui peuvent informer le jugement clinique du médecin, mais elle ne le remplace pas. Le rôle du médecin reste essentiel pour l'interprétation des informations, la prise de décisions éclairées et l'administration des soins aux patients. En somme, l'IA en réanimation est un complément, pas un substitut au médecin.


Thank you for
choosing us