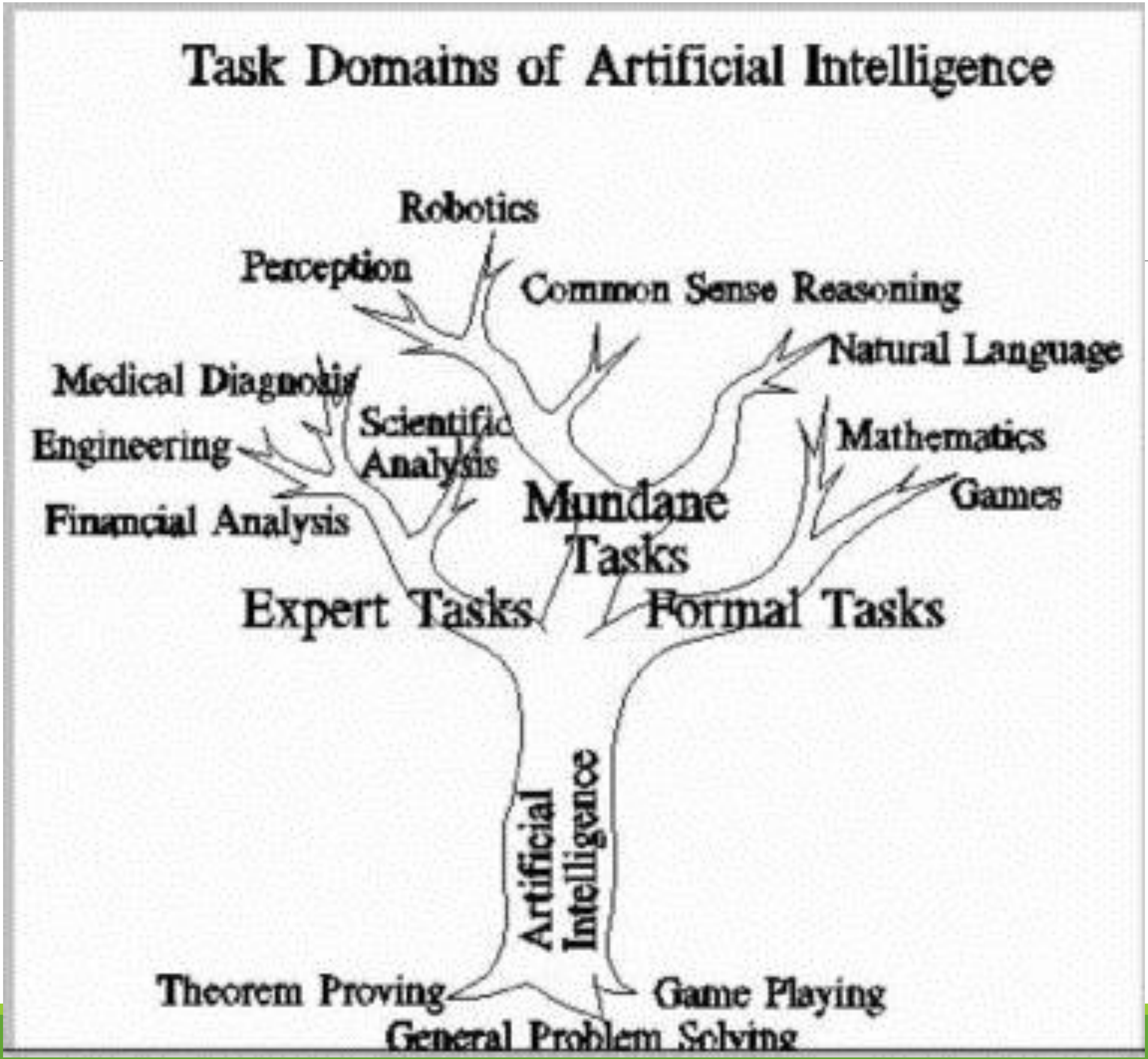
SOTUGERES
Société Tunisienne de gestion des risques en établissements de santé

la 5ème Edition des JOQSSEP
Journées de la Qualité des Soins et de la Sécurité des Patients

Intelligence artificielle: intérêt dans la prise en charge du sepsis

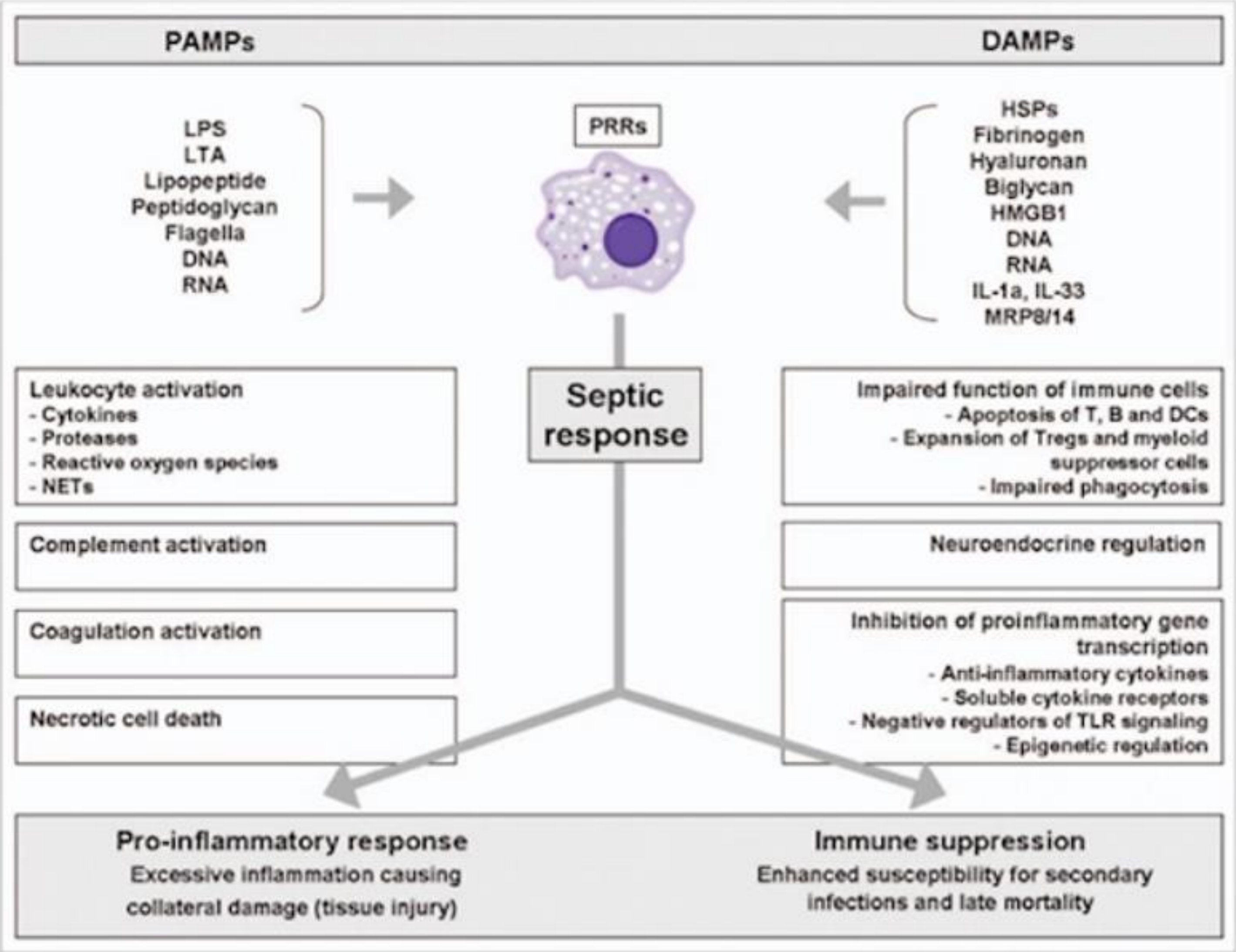
CHIHEBEDDINE ROMDHANI
MCA, ANESTHÉSIE RÉANIMATION
HÔPITAL MILITAIRE DE GABES


Task Domains of Artificial Intelligence
Robotics
Perception
Common Sense Reasoning
Natural Language
Medical Diagnosis
Scientific Analysis
Engineering
Mathematics
Games
Financial Analysis
Mundane Tasks
Expert Tasks
Formal Tasks
Artificial Intelligence
Theorem Proving
Game Playing
General Problem Solving

Host response and organ damage

Pathogen-Associated Molecular Patterns

Danger-Associated Molecular Patterns



Wiersinga et al. Virulence 2014. 5;1: 36–44

Introduction

- La santé, et particulièrement le sepsis, est un domaine d’application préférentiel de l’IA
- Cependant, le monde de la santé est l’un des secteurs ou les enjeux de l’IA sont majeurs : éthiques, responsabilité, coût …

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Expert Review of Precision Medicine and Drug Development

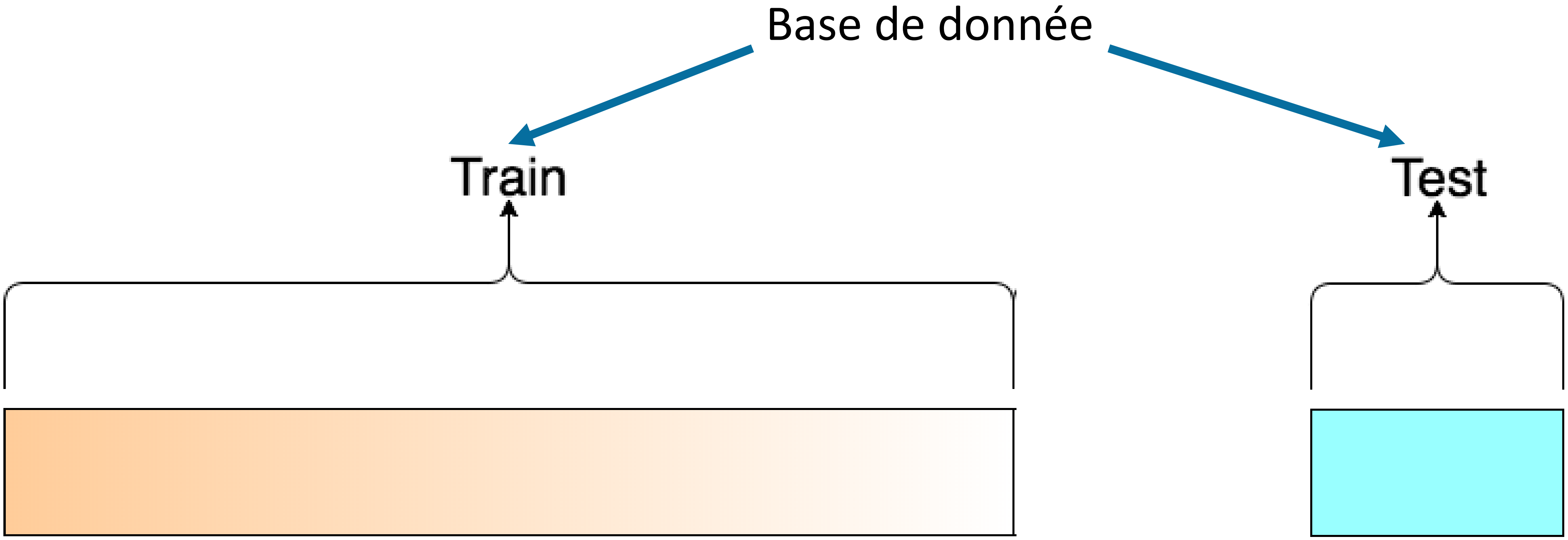
Personalized medicine in drug development and clinical practice

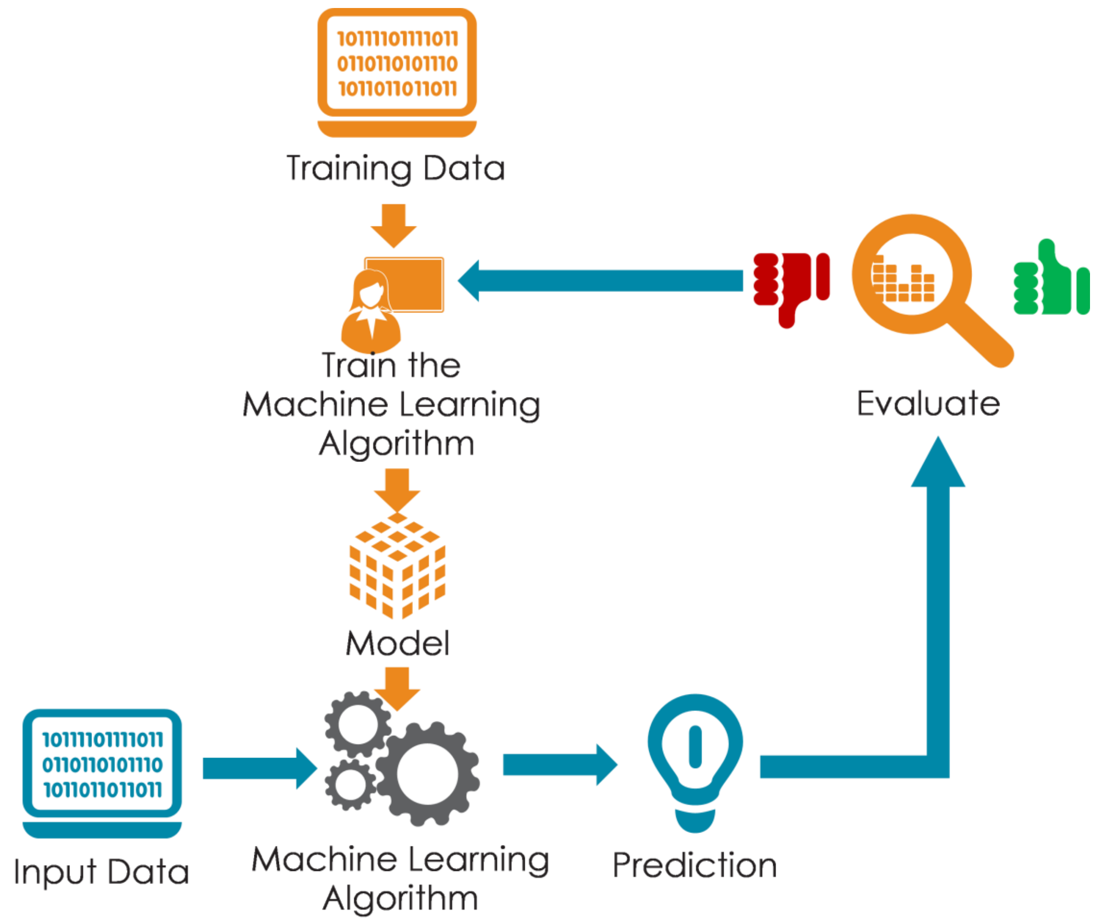
ISSN: (Print) 2380-8993 (Online) Journal homepage: https://www.tandfonline.com/loi/tepm20

Table 2. Definitions of commonly used machine-learning methods in the medical field [30] and examples of models applied in studies of patients with sepsis.

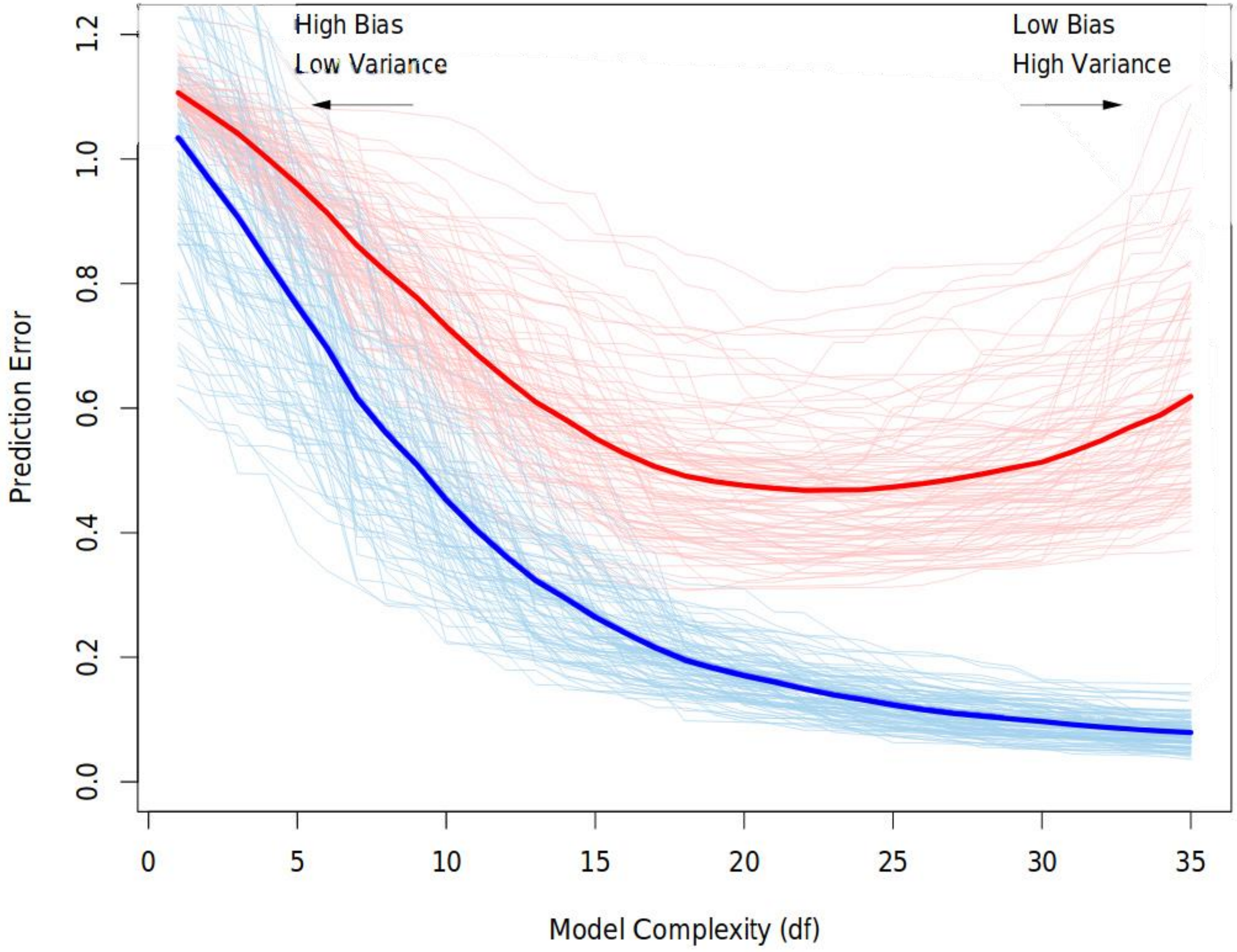
Supervised learning	Unsupervised learning	Deep learning
Aims at predicting a desired outcome based on labeled data. Used for modelling disease severity stratification and outcome.	Aims at identifying patterns in unlabeled data without knowing the outcome. Used for modelling pathophysiological mechanism and generating genomic or phenotypic profiles.	A subset of machine learning; uses multiple layers of artificial neural networks to identify patterns in data. Used for modelling disease onset according to temporal relations of events.
Support vector machine	Clustering methods	Recurrent neural networks
Random forests	• hierarchical clustering	Deep neural networks
Logistic regression	• k-means clustering	Long short-term memory neural networks
Gradient boosting	• combined mapping of multiple clustering algorithms (COMMUNAL)	
Artificial neural networks		

Intelligence artificielle





Jorge Leonel
https://medium.com/


High Bias
Low Variance
Low Bias
High Variance
Prediction Error
Model Complexity (df)
0.0
0.2
0.4
0.6
0.8
1.0
1.2
0
5
10
15
20
25
30
35

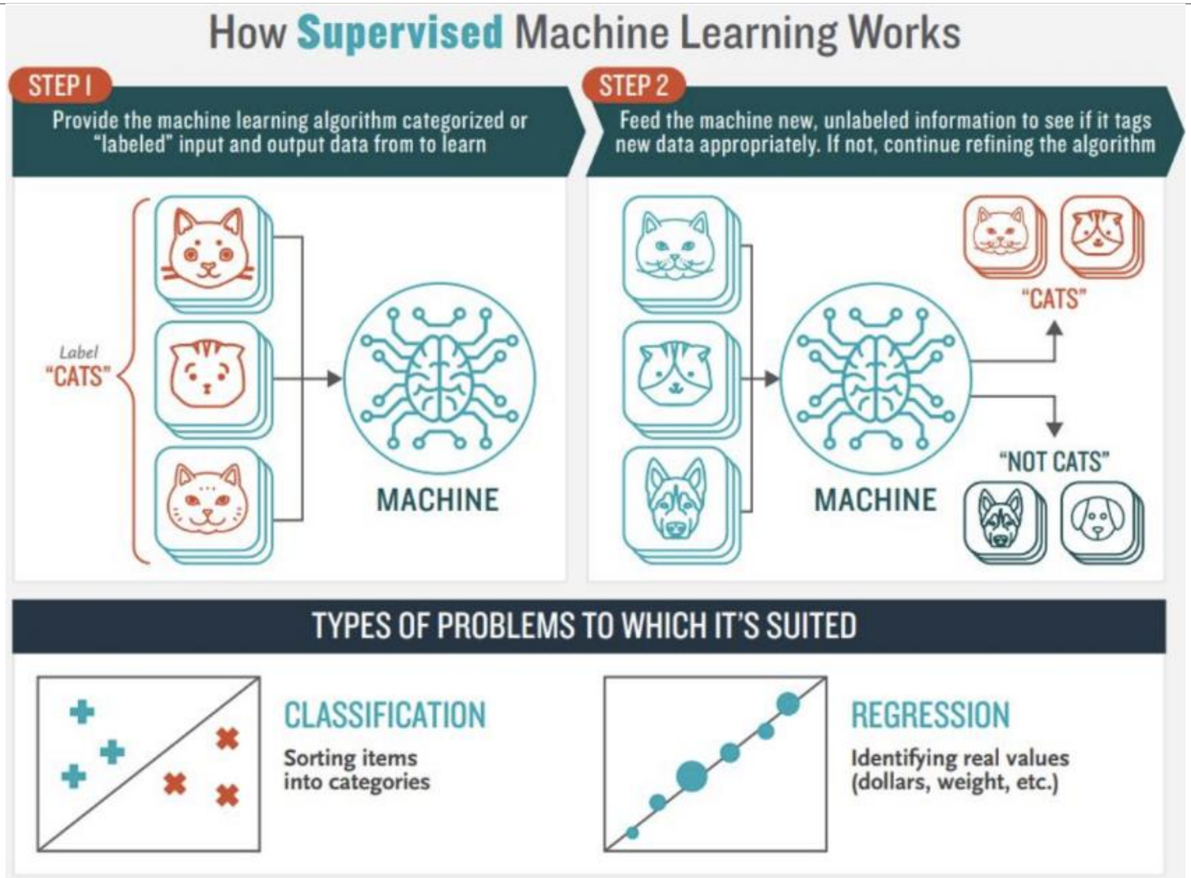

Train
Validation
Test

Apprentissage supervisé

Supervised learning

Aims at predicting a desired outcome based on labeled data. Used for modelling disease severity stratification and outcome.

Support vector machine
Random forests
Logistic regression
Gradient boosting
Artificial neural networks



Jorge Leonel

https://medium.com/@jorgesleonel/supervised-learning-c16823b00c13

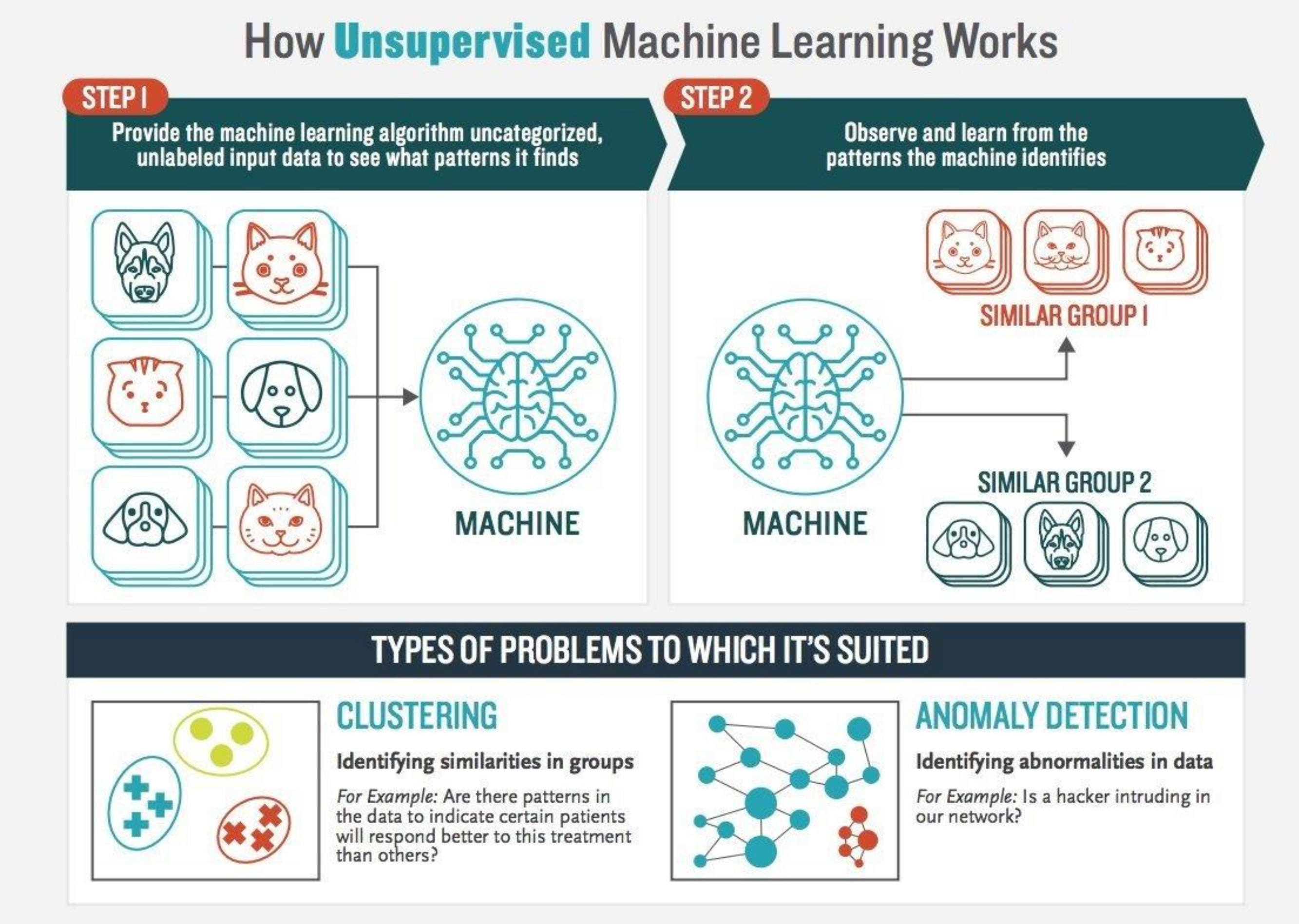
Apprentissage non supervisé

Unsupervised learning

Aims at identifying patterns in unlabeled data without knowing the outcome. Used for modelling pathophysiological mechanism and generating genomic or phenotypic profiles.

Clustering methods

- hierarchical clustering
- k-means clustering
- combined mapping of multiple clustering algorithms (COMMUNAL)



Jorge Leonel

https://medium.com/

Apprentissage ***profond*** ou Deep leanring

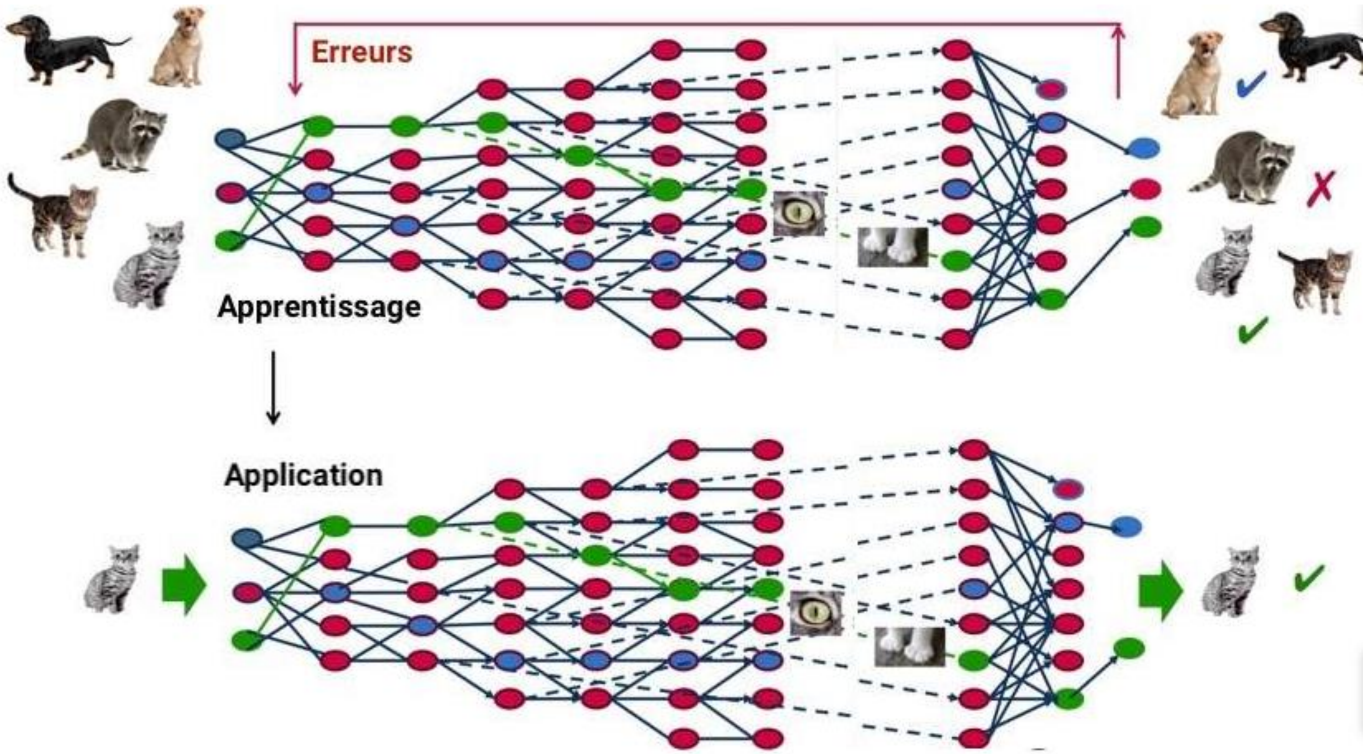
Deep learning

A subset of machine learning; uses multiple layers of artificial neural networks to identify patterns in data. Used for modelling disease onset according to temporal relations of events.

Recurrent neural networks

Deep neural networks

Long short-term memory neural networks



https://www.futura-sciences.com/tech/definitions/intelligence-artificielle-deep-learning-17262/

MÉDECINE PRÉDICTIVE

PRÉDICTION D'UNE MALADIE ET/OU DE SON ÉVOLUTION

MÉDECINE DE PRÉCISION

RECOMMANDATION DE TRAITEMENT PERSONNALISÉ

AIDE À LA DÉCISION

DIAGNOSTIQUE ET THÉRAPEUTIQUE

ROBOTS COMPAGNONS

NOTAMMENT POUR LES PERSONNES ÂGÉES OU FRAGILES

CHIRURGIE ASSISTÉE PAR ORDINATEUR

PRÉVENTION

en population générale

- ANTICIPATION D'UNE ÉPIDÉMIE
- PHARMACOVIGILANCE

Introduction

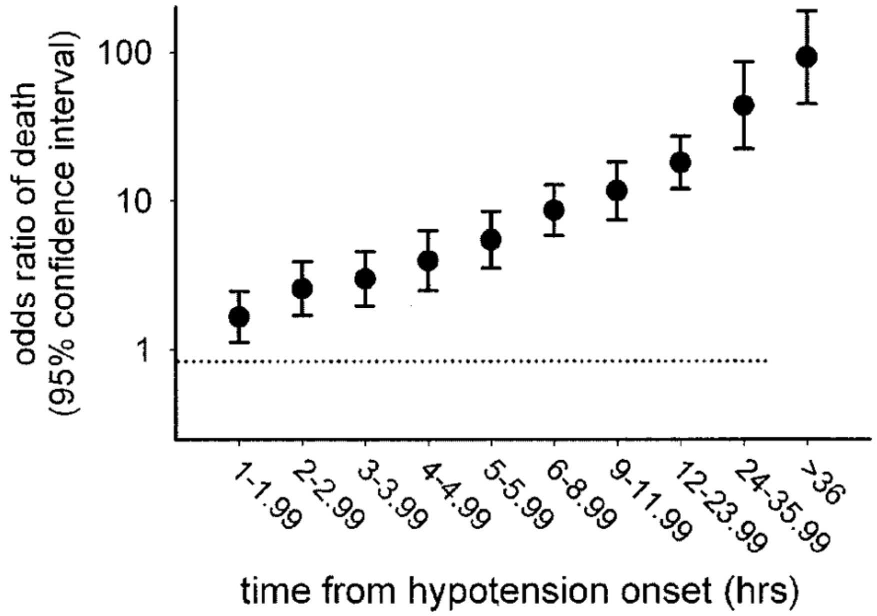
- L’IA peut être utilisé :
  - En pharmacologie
  - Imagerie médicale
  - L’analyse de risques
  - Prédiction
  - Aide au diagnostic

MÉDECINE PRÉDICTIVE

PRÉDICTION D'UNE MALADIE
ET/OU DE SON ÉVOLUTION

Duration of hypotension before initiation of effective antimicrobial therapy is the critical determinant of survival in human septic shock*

Anand Kumar, MD; Daniel Roberts, MD; Kenneth E. Wood, DO; Bruce Light, MD; Joseph E. Parrillo, MD; Satendra Sharma, MD; Robert Suppes, BSc; Daniel Feinstein, MD; Sergio Zanotti, MD; Leo Taiberg, MD; David Gurka, MD; Aseem Kumar, PhD; Mary Cheang, MSc



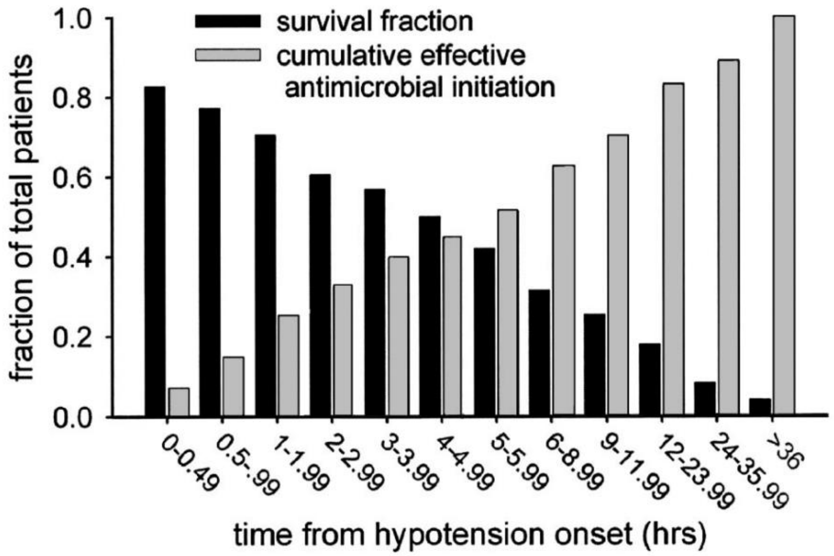


Figure 1. Cumulative effective antimicrobial initiation following onset of septic shock-associated hypotension and associated survival. The x-axis represents time (hrs) following first documentation of septic shock-associated hypotension. *Black bars* represent the fraction of patients surviving to hospital discharge for effective therapy initiated within the given time interval. The *gray bars* represent the cumulative fraction of patients having received effective antimicrobials at any given time point.

CLINICAL AND VACCINE IMMUNOLOGY, July 2008, p. 1089–1094 Vol. 15, No. 7
1556-6811/08/$08.00+0 doi:10.1128/CVI.00486-07

American Society for Microbiology | Clinical and Vaccine Immunology® Published 2006-2017

Presymptomatic Prediction of Sepsis in Intensive Care Unit Patients▽

R. A. Lukaszewski,[1]* A. M. Yates,[1] M. C. Jackson,[1] K. Swingler,[2] J. M. Scherer,[1] A. J. Simpson,[1] P. Sadler,[3] P. McQuillan,[3] R. W. Titball,[5] T. J. G. Brooks,[4] and M. J. Pearce[1]

Dstl Porton Down, Salisbury, Wiltshire, United Kingdom SP4 0JQ[1]; INCITE Group, University of Stirling, Stirling, Scotland[2]; Department of Critical Care, Queen Alexandra Hospital, Cosham, Portsmouth, Hampshire, United Kingdom PO6 3LY[3]; HPA Centre for Emergency Preparedness and Response, Porton Down, Salisbury, Wiltshire, United Kingdom[4]; and School of Biosciences, Geoffrey Pope Building, University of Exeter, Exeter, United Kingdom[5]

Received 22 November 2007/Returned for modification 30 January 2008/Accepted 29 April 2008

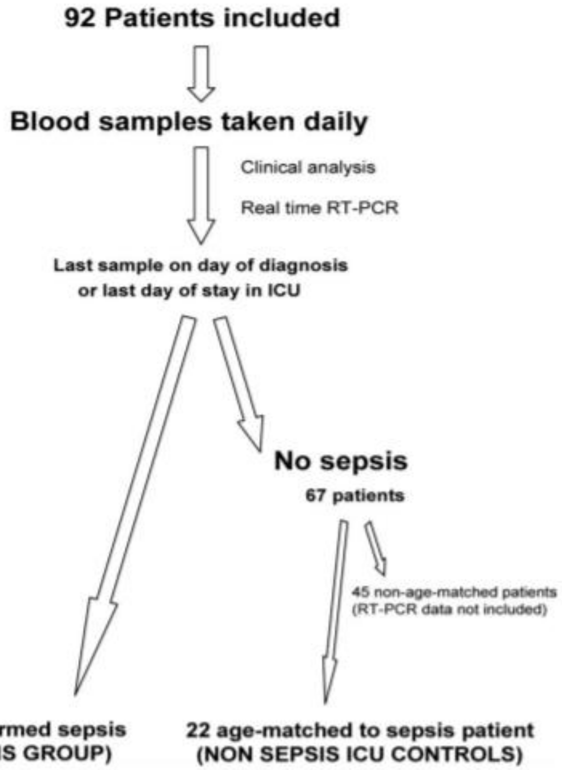
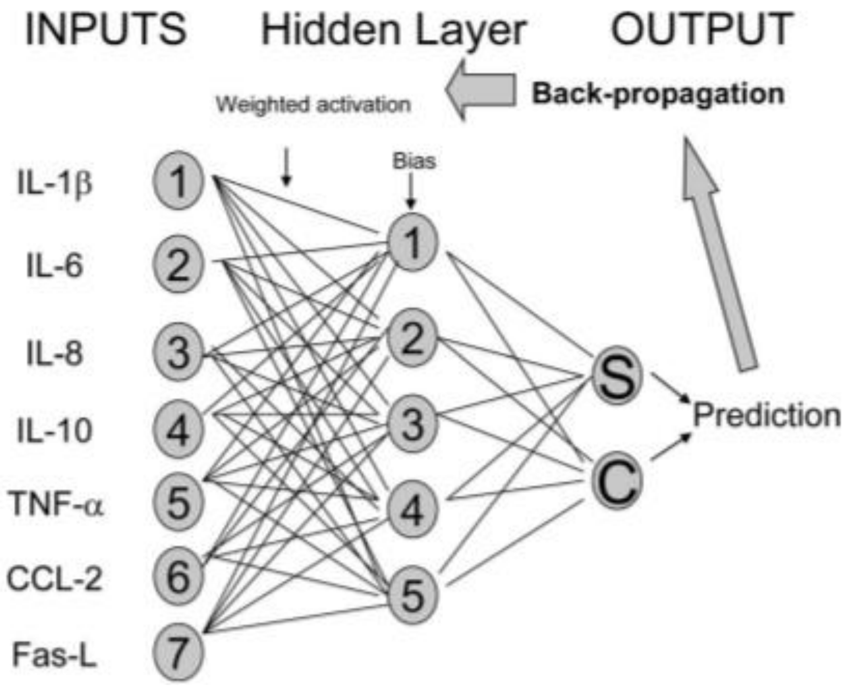


FIG. 1. Summary of the study design.



Clinical and Vaccine Immunology, July 2008, p. 1089–1094 Vol. 15, No. 7
1556-6811/08/$08.00+0 doi:10.1128/CVI.00486-07

Clinical and Vaccine Immunology® Published 2006-2017

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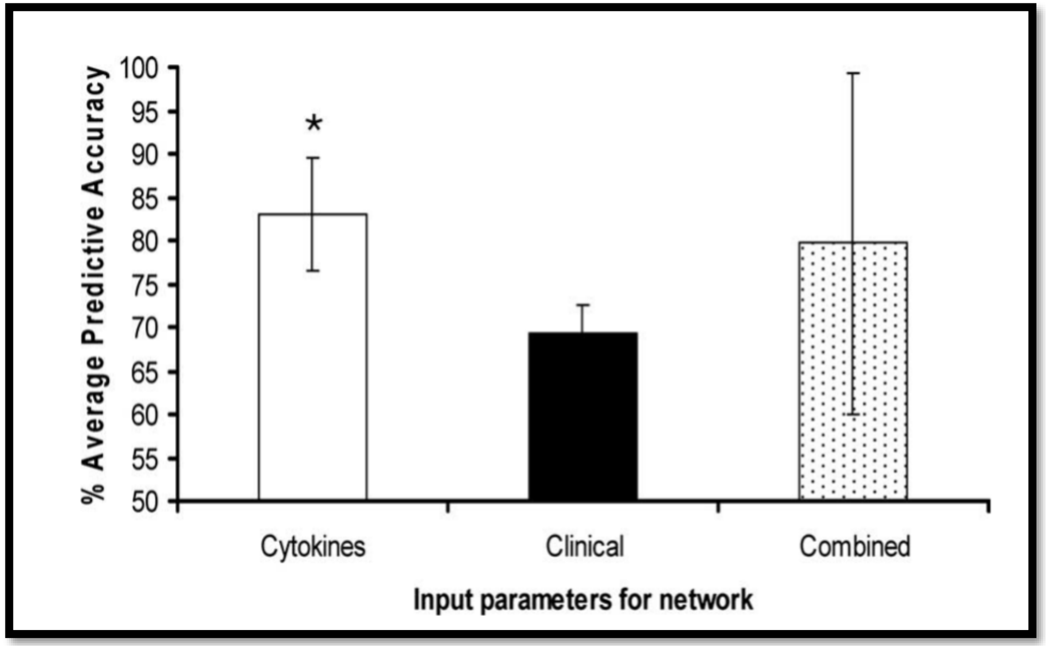
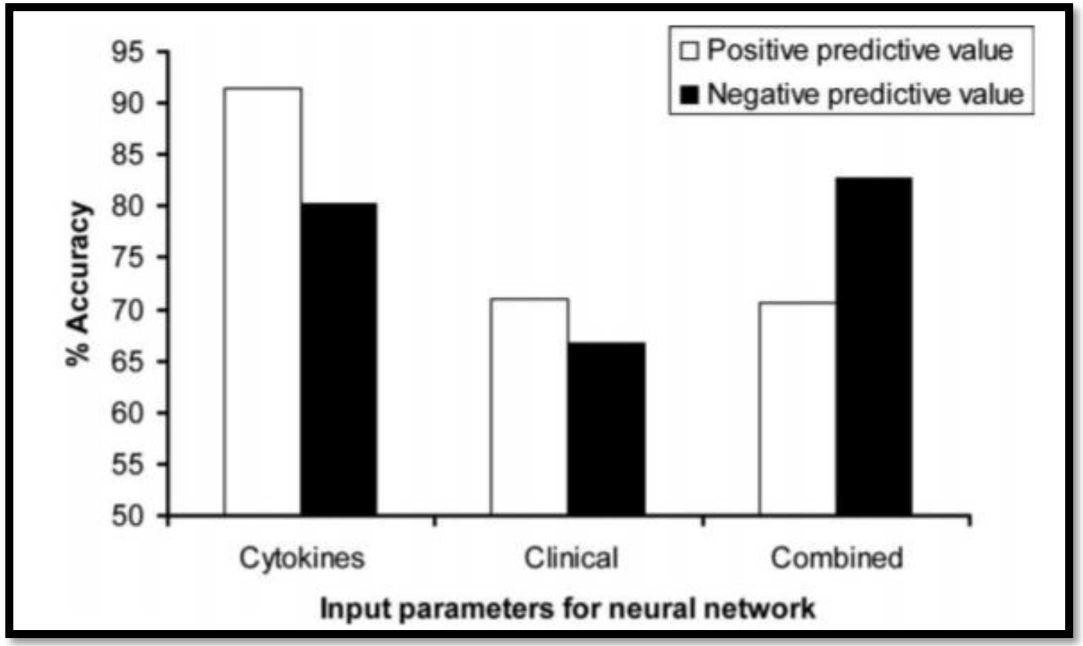




PeerJ

Automated electronic medical record sepsis detection in the emergency department

Su Q. Nguyen[1,4], Edwin Mwakalindile[1,5], James S. Booth[2], Vicki Hogan[3], Jordan Morgan[2], Charles T. Prickett[2], John P. Donnelly[2] and Henry E. Wang[2]

- Une alerte automatique / Dossier informatisé
  - SIRS + (PAS < 90 mmHg ou lactate > 2)
  - 795 alertes durant 3 mois
    - 300 alertes analysées
      - VPP 44,7%

DOI 10.7717/peerj.343

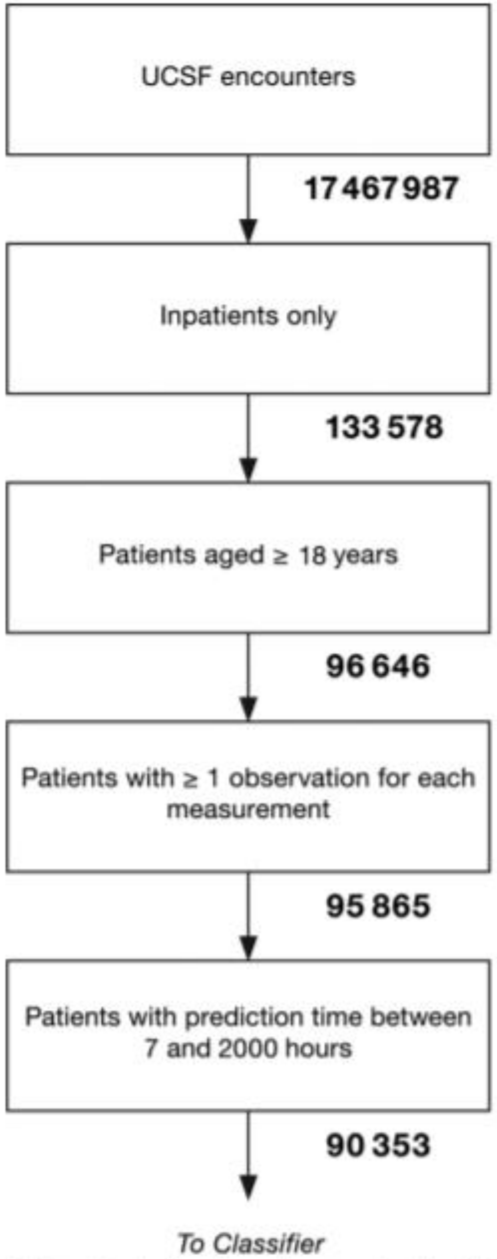


Figure 1 Patient inclusion flow diagram for the UCSF dataset. UCSF, University of California, San Francisco.

Open Access Research

BMJ Open

Multicentre validation of a sepsis prediction algorithm using only vital sign data in the emergency department, general ward and ICU

Qingqing Mao,[1] Melissa Jay,[1] Jana L Hoffman,[1] Jacob Calvert,[1] Christopher Barton,[2] David Shimabukuro,[3] Lisa Shieh,[4] Uli Chettipally,[2,5] Grant Fletcher,[6] Yaniv Kerem,[7,8] Yifan Zhou,[1,9] Ritankar Das[1]

Gradient tree boosting machine learning algorithm

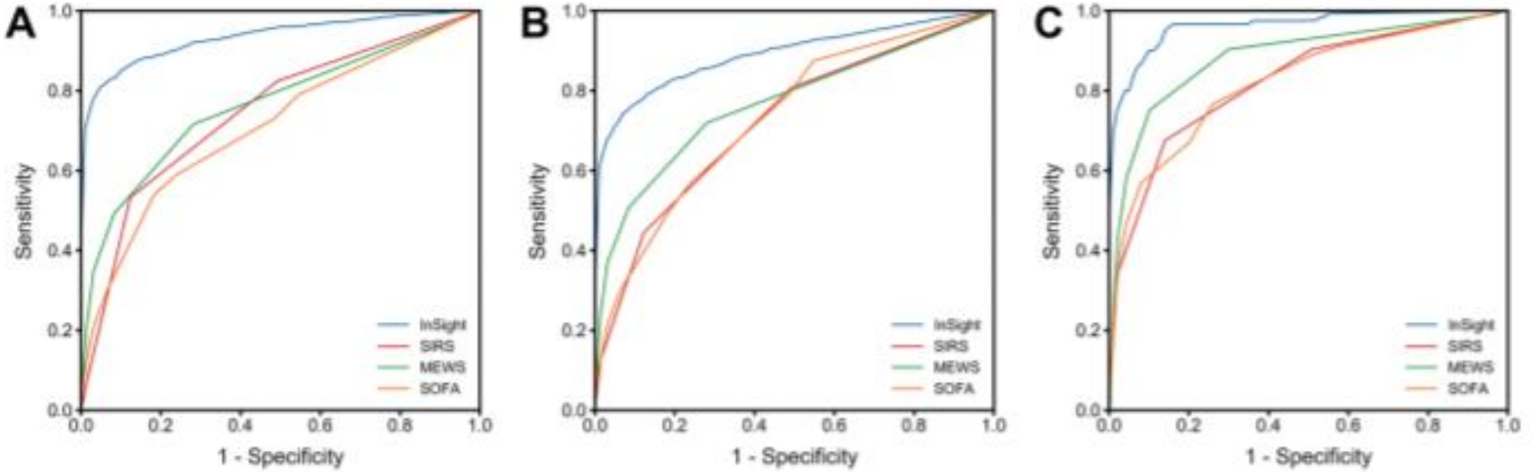


Figure 2 ROC curves for *InSight* and common scoring systems at the time of (A) sepsis onset, (B) severe sepsis onset and (C) 4 hours before septic shock onset. MEWS, Modified Early Warning Score; ROC, receiver operating characteristic; SIRS, systemic inflammatory response syndrome; SOFA, Sequential Organ Failure Assessment.

Mao Q, *et al. BMJ Open* 2018;**8**:e017833. doi:10.1136/bmjopen-2017-017833

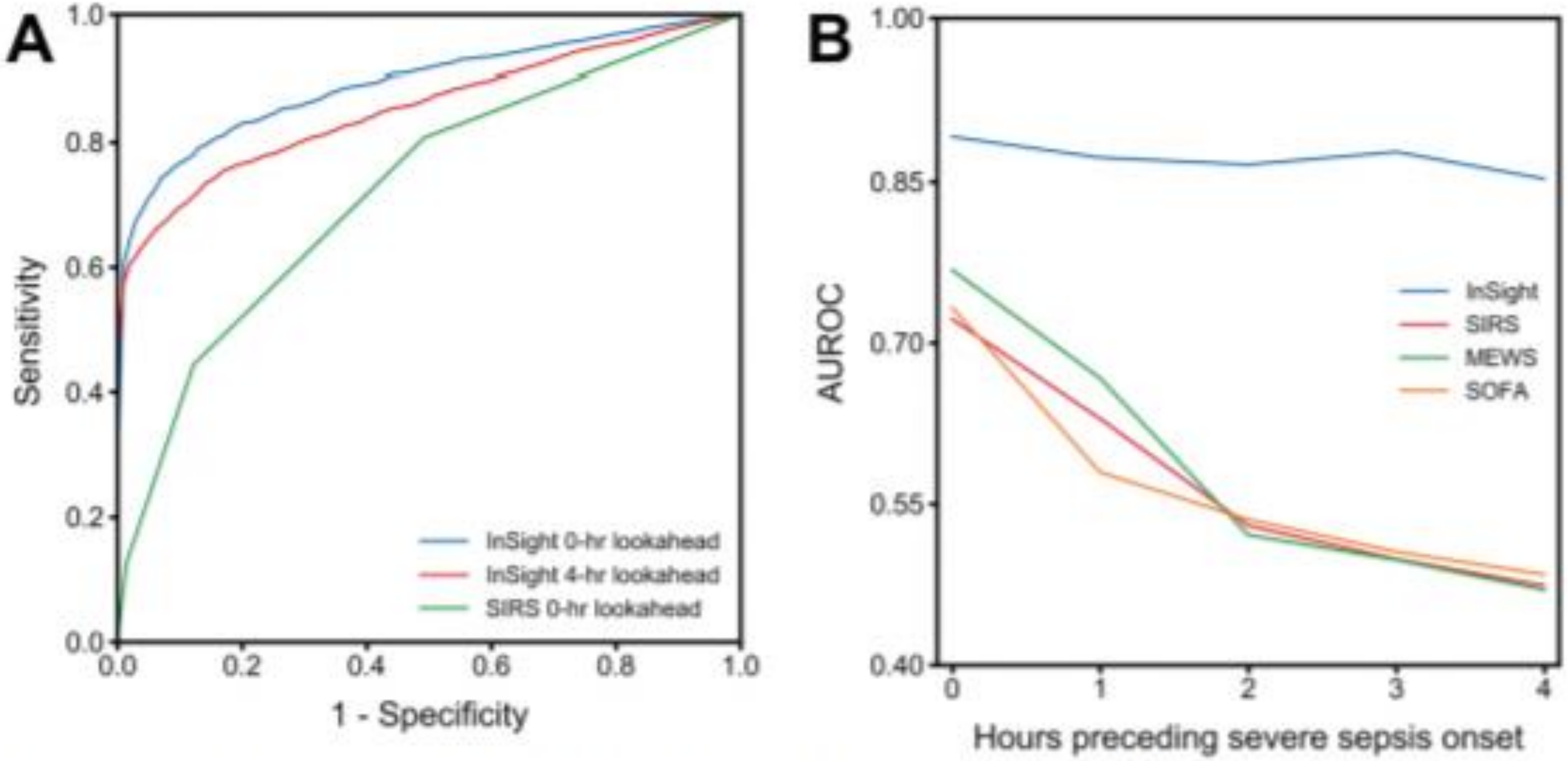
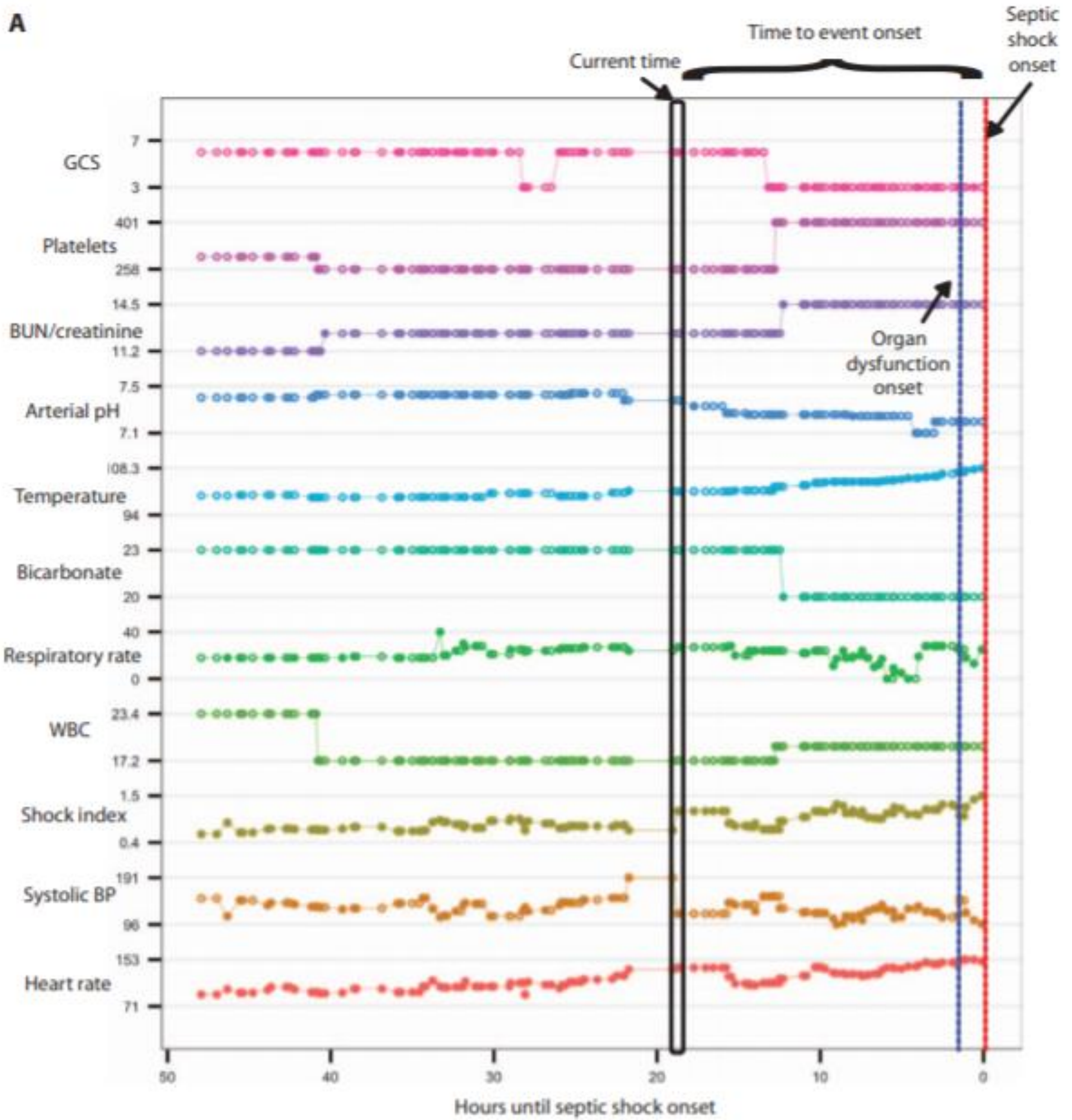


Figure 3 (A) ROC detection (0 hour, blue) and prediction (4 hours prior to onset, red) curves using *InSight* and ROC detection (0 hour, green) curve for SIRS, with the severe sepsis gold standard. (B) Predictive performance of *InSight* and comparators, using the severe sepsis gold standard, as a function of time prior to onset. AUROC, area under the receiver operating characteristic; ROC, receiver operating characteristic; MEWS, Modified Early Warning Score; SIRS, systemic inflammatory response syndrome; SOFA, Sequential Organ Failure Assessment.



SEPSIS

A targeted real-time early warning score (TREWScore) for septic shock

Katharine E. Henry,[1] David N. Hager,[2] Peter J. Pronovost,[3,4,5] Suchi Saria[1,3,5,6]*

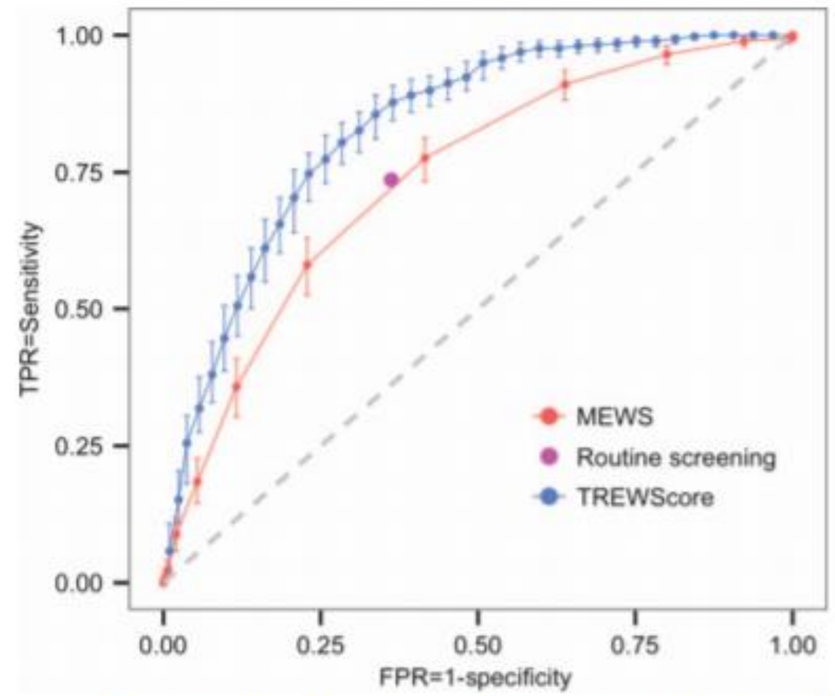


Fig. 2. ROC for detection of septic shock before onset in the validation set. The ROC curve for TREWScore is shown in blue, with the ROC curve for MEWS in red. The sensitivity and specificity performance of the routine screening criteria is indicated by the purple dot. Normal 95% CIs are shown for TREWScore and MEWS. TPR, true-positive rate; FPR, false-positive rate.

Machine Learning Methods for Septic Shock Prediction

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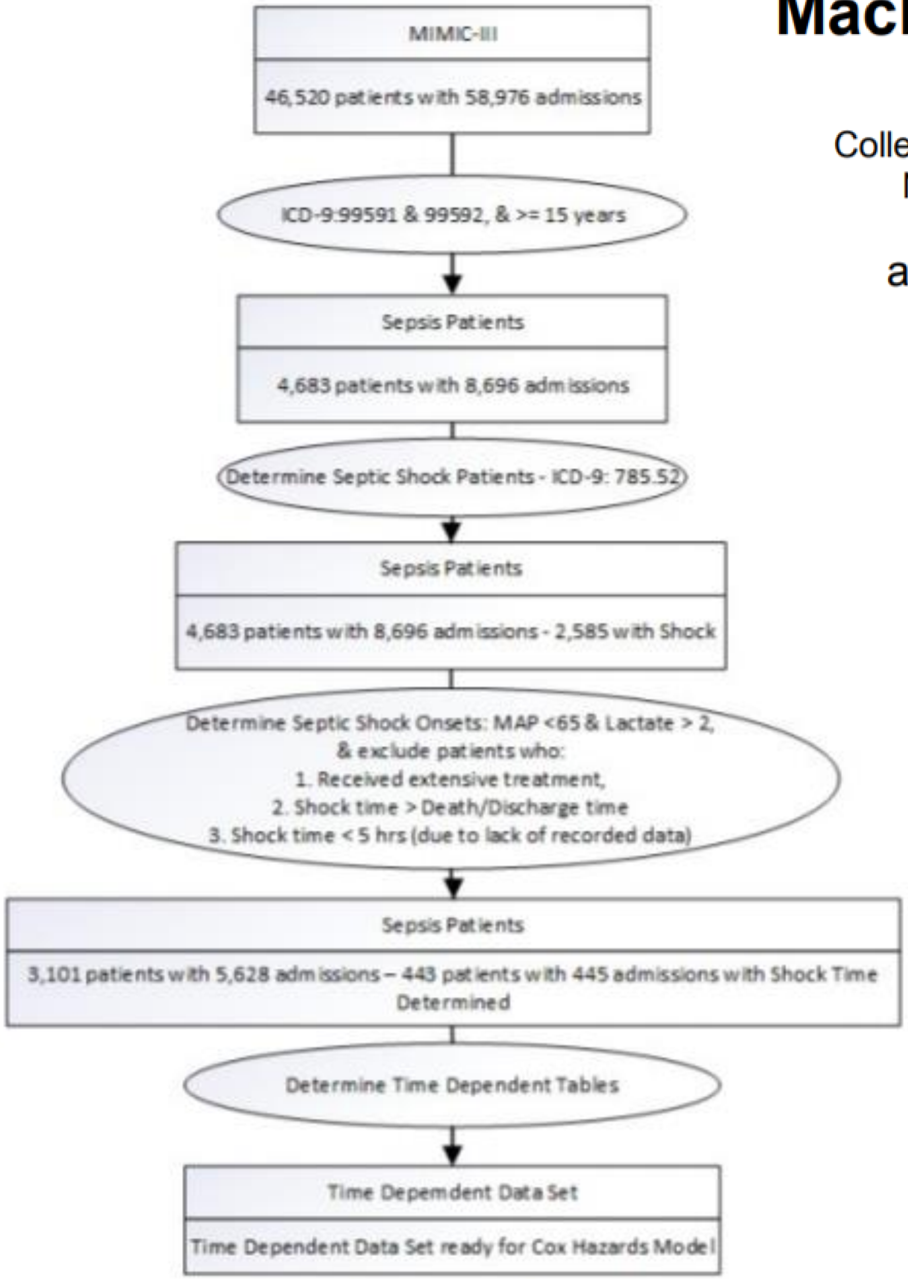

Figure 1. Patients' selection process.

Cox Enhanced Random Forest Prediction Model

Table 1. Feature List

List of Features	
Feature Name	***Feature Description***
Albumin	Albumin checks liver and kidney function
Creatinine	The level of creatinine in the blood
DBP	Diastolic Blood Pressure
GCS	Glasgow coma score (GCS)
HR	Heart rate
Lactate	The presence of lactic acid in the body
MAP	Mean Arterial Pressure
RR	Respiratory rate
SBP	Systolic blood pressure
SI	HR/SBP ratio
SpO_2	Estimate of oxygen concentration in blood
Temperature	Body Temperature
WBC	White blood cell count

AIVR 2018, November 23–25, 2018, Nagoya, Japan.

ACM ISBN 978-1-4503-6641-0/18/11…$15.00
DOI: https://doi.org/10.1145/3293663.3293673

Machine Learning Methods for Septic Shock Prediction

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	Précision	Sensibilité	Spécificité
Cox Enhanced Random Forest Prediction Model	95 %	89 %	97 %
Outil de détection précoce classique : • SIRS • suspicion d'infection • Hypotension ou hyperlactatemie	-	64 %	74 %
A targeted real-time early warning score (TREW Score)	83 %	85 %	67 %
InSight	96 %	80 %	95 %

AIVR 2018, November 23–25, 2018, Nagoya, Japan.

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DOI: https://doi.org/10.1145/3293663.3293673

Artificial Intelligence In Medicine xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Artificial Intelligence In Medicine

journal homepage: www.elsevier.com/locate/artmed

Accurate prediction of blood culture outcome in the intensive care unit using long short-term memory neural networks

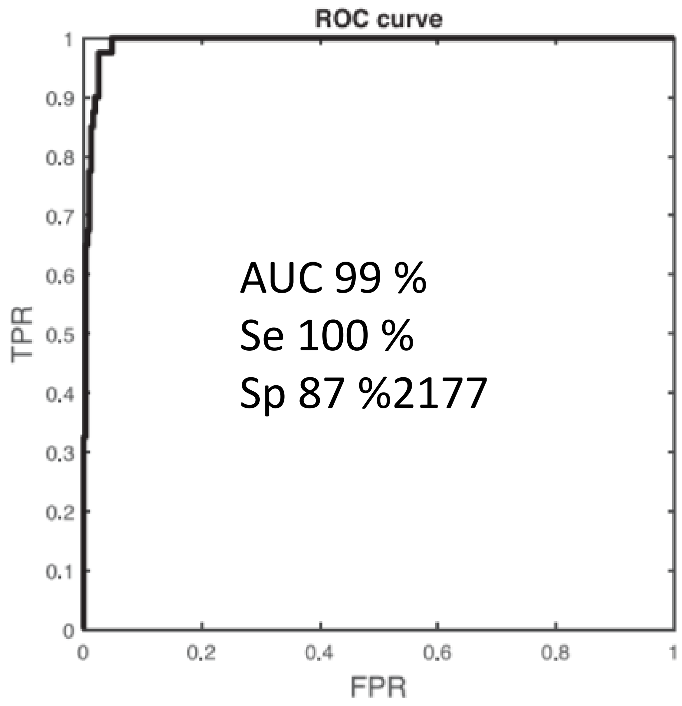
Tom Van Steenkiste[a], Joeri Ruyssinck[a,*], Leen De Baets[a], Johan Decruyenaere[b], Filip De Turck[a], Femke Ongenae[a], Tom Dhaene[a]

[a] Ghent University – imec, IDLab, Department of Information Technology, Technologiepark 15, B-9052, Ghent, Belgium
[b] Ghent University Hospital, Department of Internal Medicine, De Pintelaan 185, B-9050 Ghent, Belgium

2177 admission en réanimation

Table 1
Overview of included clinical parameters. If the sampling frequency of a variable is higher than one per hour, we subsample the data using the approach described within the main text.

Variable	Sampling strategy
Temperature [°C]	max
Blood thrombocyte count	min
Blood leukocyte count	mean
C-reactive protein concentration [mg/l]	max
Sepsis-related organ failure assessment	max
Heart rate [bpm]	max
Respiratory rate [rpm]	max
Int. normalized ratio of prothrombine time	max
Mean systemic arterial pressure [mmHg]	max

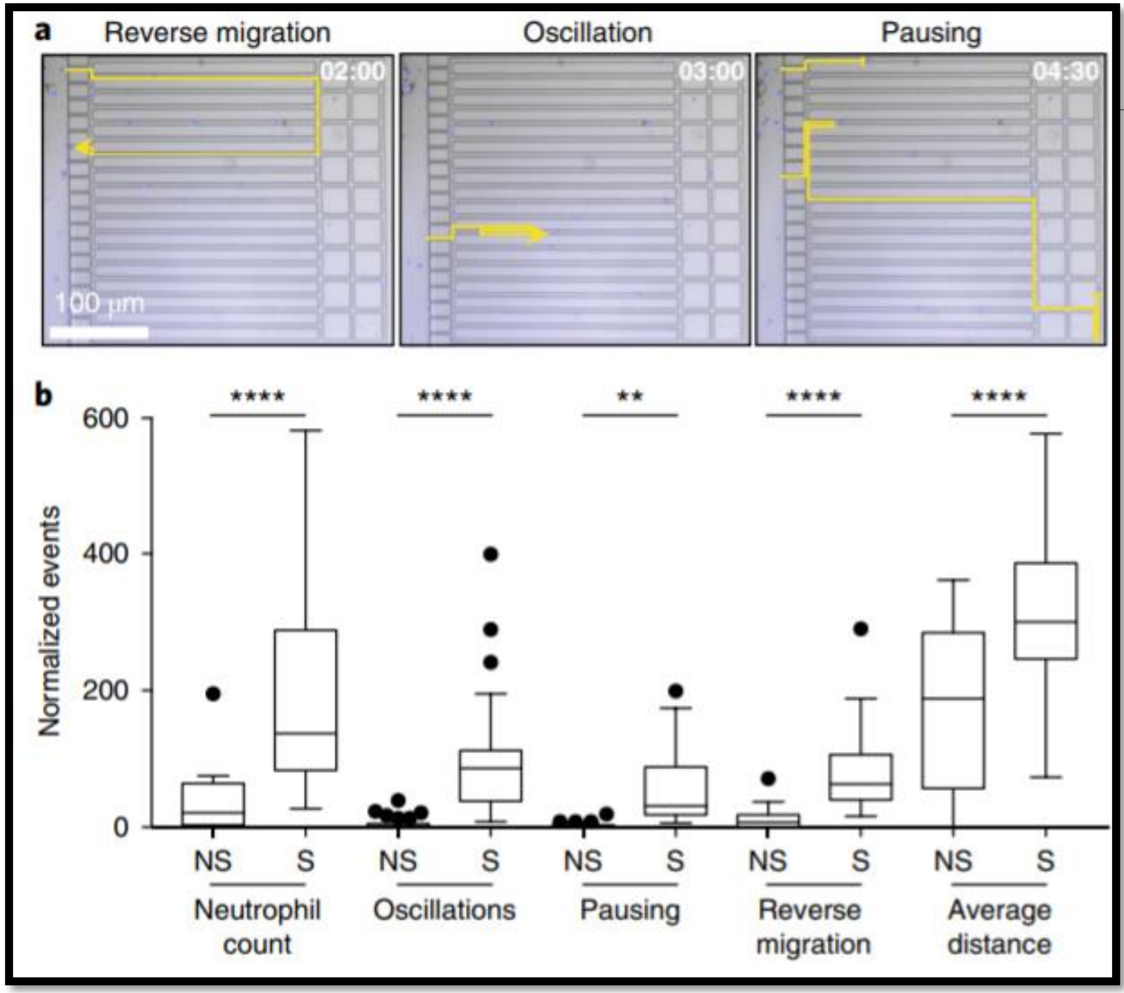


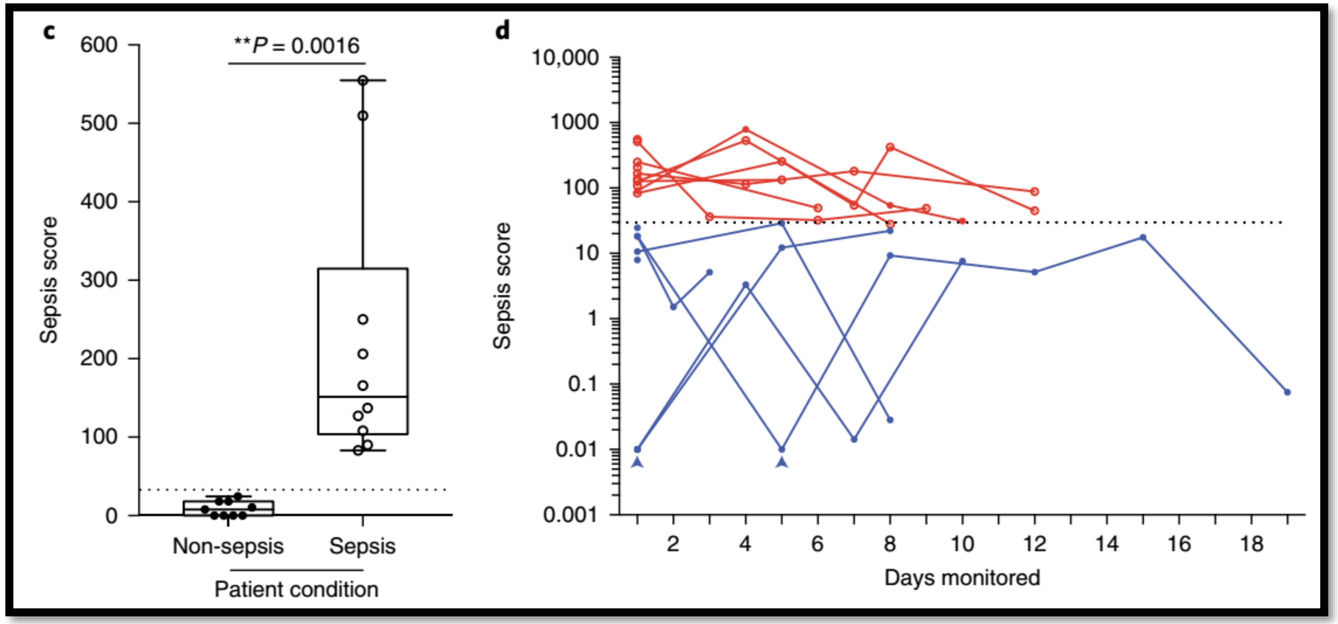
Artif Intell Med. 2019 Jun;97:38-43. doi: 10.1016/j.artmed.2018.10.008. Epub 2018 Nov 9.

nature biomedical engineering
ARTICLES
https://doi.org/10.1038/s41551-018-0208-z

Diagnosis of sepsis from a drop of blood by measurement of spontaneous neutrophil motility in a microfluidic assay

Felix Ellett[1,2,3,4], Julianne Jorgensen[1,4], Anika L. Marand[1,4], Yuk Ming Liu[2,3,4], Myriam M. Martinez[4], Vicki Sein[3,4], Kathryn L. Butler[3,4], Jarone Lee[3,4,5] and Daniel Irimia[1,2,3,4*]





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Expert Review of Precision Medicine and Drug Development

Personalized medicine in drug development and clinical practice

ISSN: (Print) 2380-8993 (Online) Journal homepage: https://www.tandfonline.com/loi/tepm20

Table 3. Some key studies on the applications of artificial intelligence algorithms for diagnosis and risk stratification in sepsis.

Reference	Country	Study type	Period	Data	N	Sepsis identification	Models	Application	Comparison	Sens. (%)	Spec. (%)	AUROC	External validation
Delahanty et al. 2018 [31]	USA	Retrospective	2016–2017	ER 49 Tenet Healthcare Hospitals	2,759,529	Sepsis-3	Gradient boosting	Predicts risk of sepsis and in-hospital mortality.	**MLA**	**67.7**	**96.4**	**0.93**	No
									SIRS	40.4	93.6	0.78	
									MEWS	11.5	99.1	0.62	
									qSOFA	3.7	99.8	0.62	
									SOFA	49.2	92.9	0.78	
Taylor et al. 2016 [32]	USA	Retrospective	2013–2014	ER Yale-New Haven Hospital	4676	SIRS, ICD-9	Random forest	Predicts in-hospital mortality.	**MLA**	–	–	**0.86**	No
									CURB-65	–	–	0.73	
									MEDS	–	–	0.71	
									mREMS	–	–	0.72	

To cite this article: Pedro Palma & Jordi Rello (2019) Precision medicine for the treatment of sepsis: recent advances and future prospects, Expert Review of Precision Medicine and Drug Development, 4:4, 205-213, DOI: 10.1080/23808993.2019.1626714


MÉDECINE DE PRÉCISION
RECOMMANDATION DE TRAITEMENT PERSONNALISÉ

Expert Review of Precision Medicine and Drug Development

Personalized medicine in drug development and clinical practice

ISSN: (Print) 2380-8993 (Online) Journal homepage: https://www.tandfonline.com/loi/tepm20

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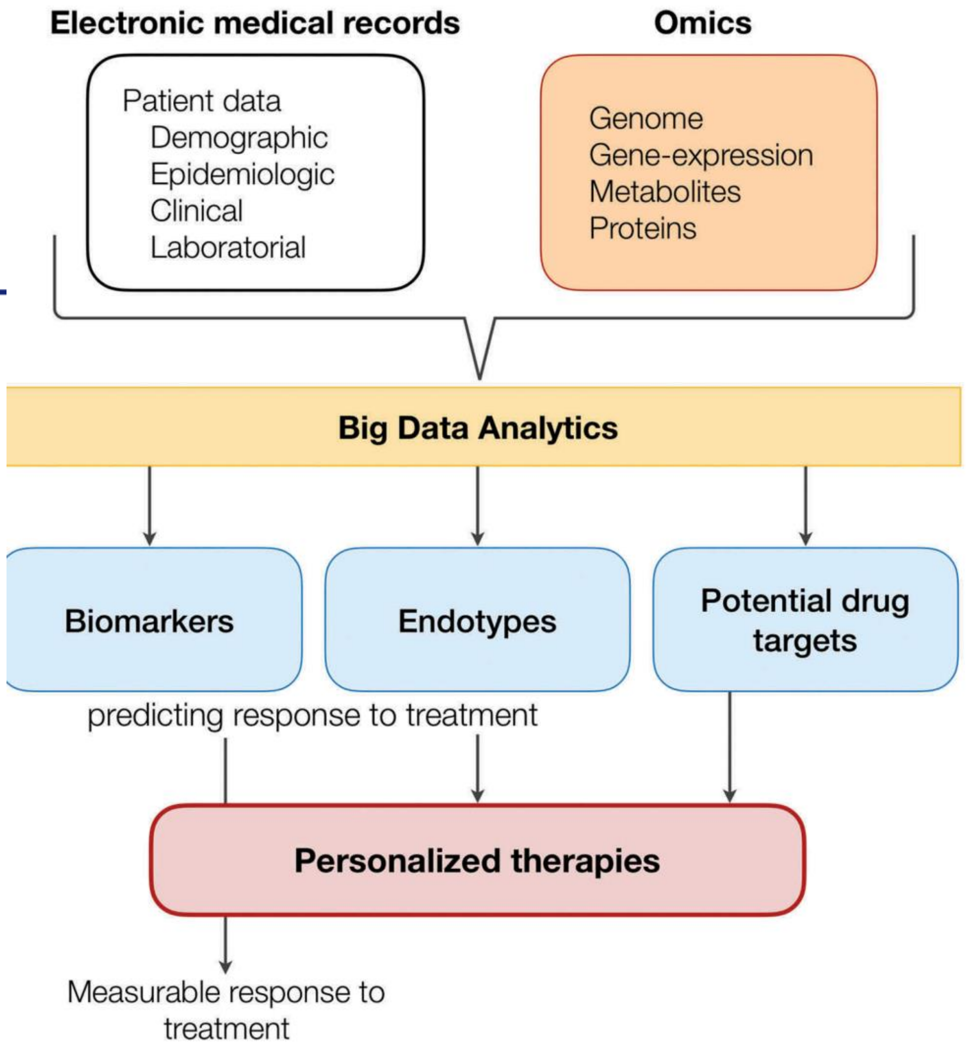


ORIGINAL ARTICLE

The NEW ENGLAND JOURNAL of MEDICINE

Drotrecogin Alfa (Activated) for Adults with Severe Sepsis and a Low Risk of Death

- 2640 patients 2002 à 04
- Pas de différence sur la mortalité
- **Risque hémorragique grave** significativement plus important dans groupe PCA

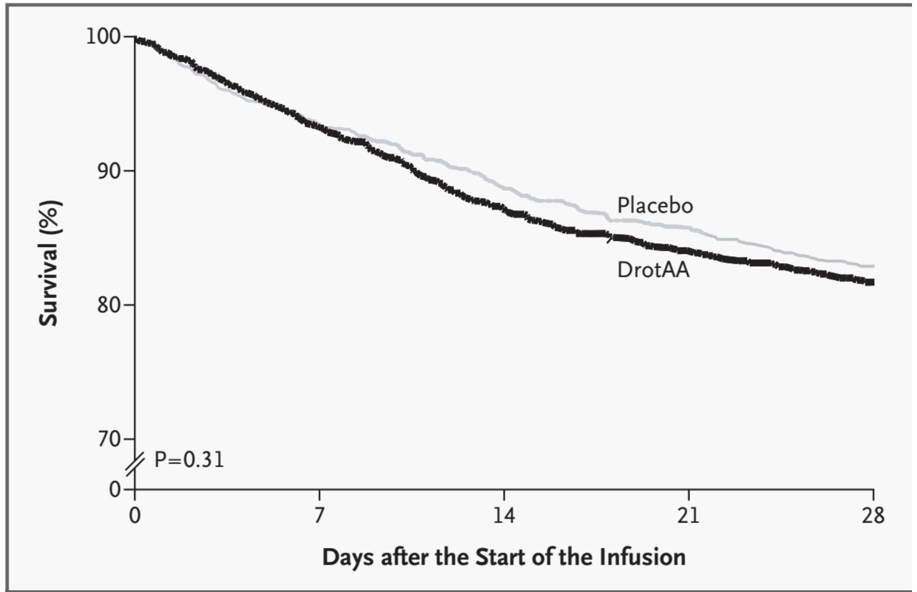


Figure 2. Kaplan–Meier Estimates of Survival among 1316 Patients with Severe Sepsis in the Drotrecogin Alfa (Activated) (DrotAA) Group and 1297 Patients in the Placebo Group.

There was no significant difference between the treatment groups in survival at 28 days (P=0.31 by the log-rank test).

N Engl J Med 2005;353:1332-41.

Recommandations actuelles

CONFERENCE REPORTS AND EXPERT PANEL

CrossMark

Surviving Sepsis Campaign: International Guidelines for Management of Sepsis and Septic Shock: 2016

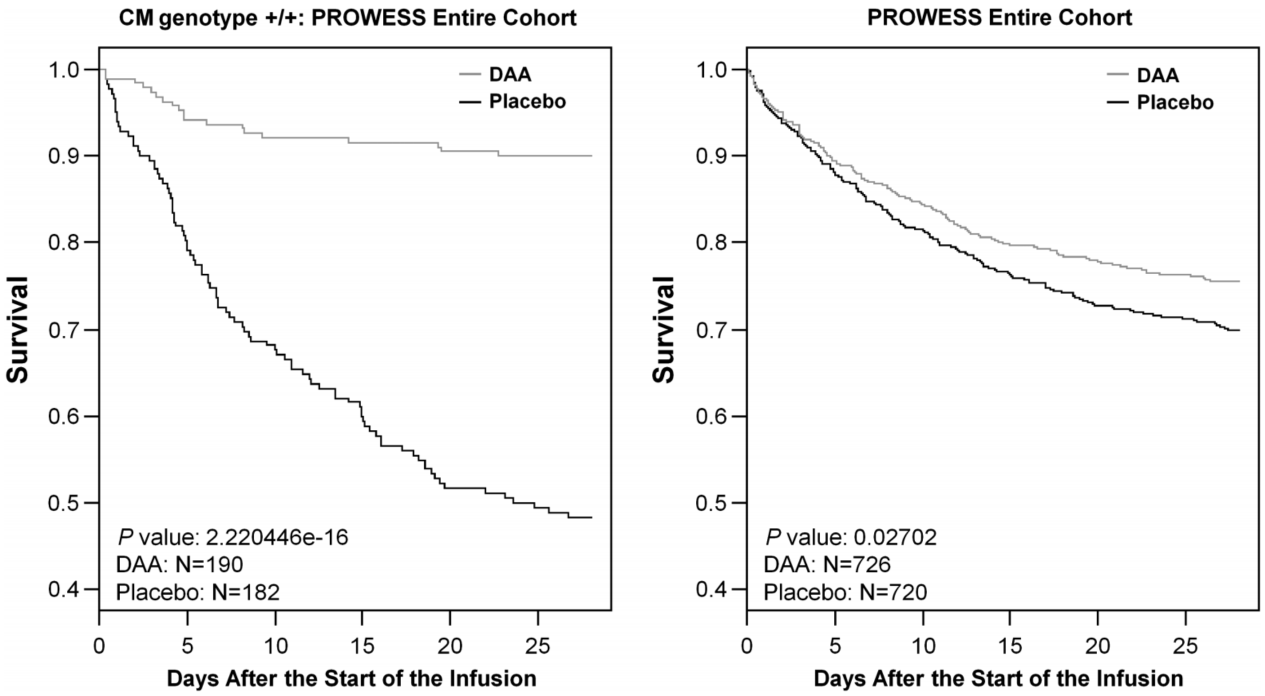
Surviving Sepsis Campaign: International guidelines for management of severe sepsis and septic shock: 2008

R. Phillip Dellinger, MD; Mitchell M. Levy, MD; Jean M. Carlet, MD; Julian Bion, MD; Margaret M. Parker, MD; Roman Jaeschke, MD; Konrad Reinhart, MD; Derek C. Angus, MD, MPH; Christian Brun-Buisson, MD; Richard Beale, MD; Thierry Calandra, MD, PhD; Jean-Francois Dhainaut, MD; Herwig Gerlach, MD; Maurene Harvey, RN; John J. Marini, MD; John Marshall, MD; Marco Ranieri, MD; Graham Ramsay, MD; Jonathan Sevransky, MD; B. Taylor Thompson, MD; Sean Townsend, MD; Jeffrey S. Vender, MD; Janice L. Zimmerman, MD; Jean-Louis Vincent, MD, PhD; for the International Surviving Sepsis Campaign Guidelines Committee

Recombinant activated protein C, which was originally recommended in the 2004 and 2008 SSC guidelines, was not shown to be effective for adult patients with septic shock by the PROWESS-SHOCK trial, and was withdrawn from the market [345].

Surviving Sepsis Campaign

Beyond single-marker analyses: mining whole genome scans for insights into treatment responses in severe sepsis



The Pharmacogenomics Journal (2012), 1–9

JAMA | Original Investigation | CARING FOR THE CRITICALLY ILL PATIENT

Effect of Targeted Polymyxin B Hemoperfusion on 28-Day Mortality in Patients With Septic Shock and Elevated Endotoxin Level

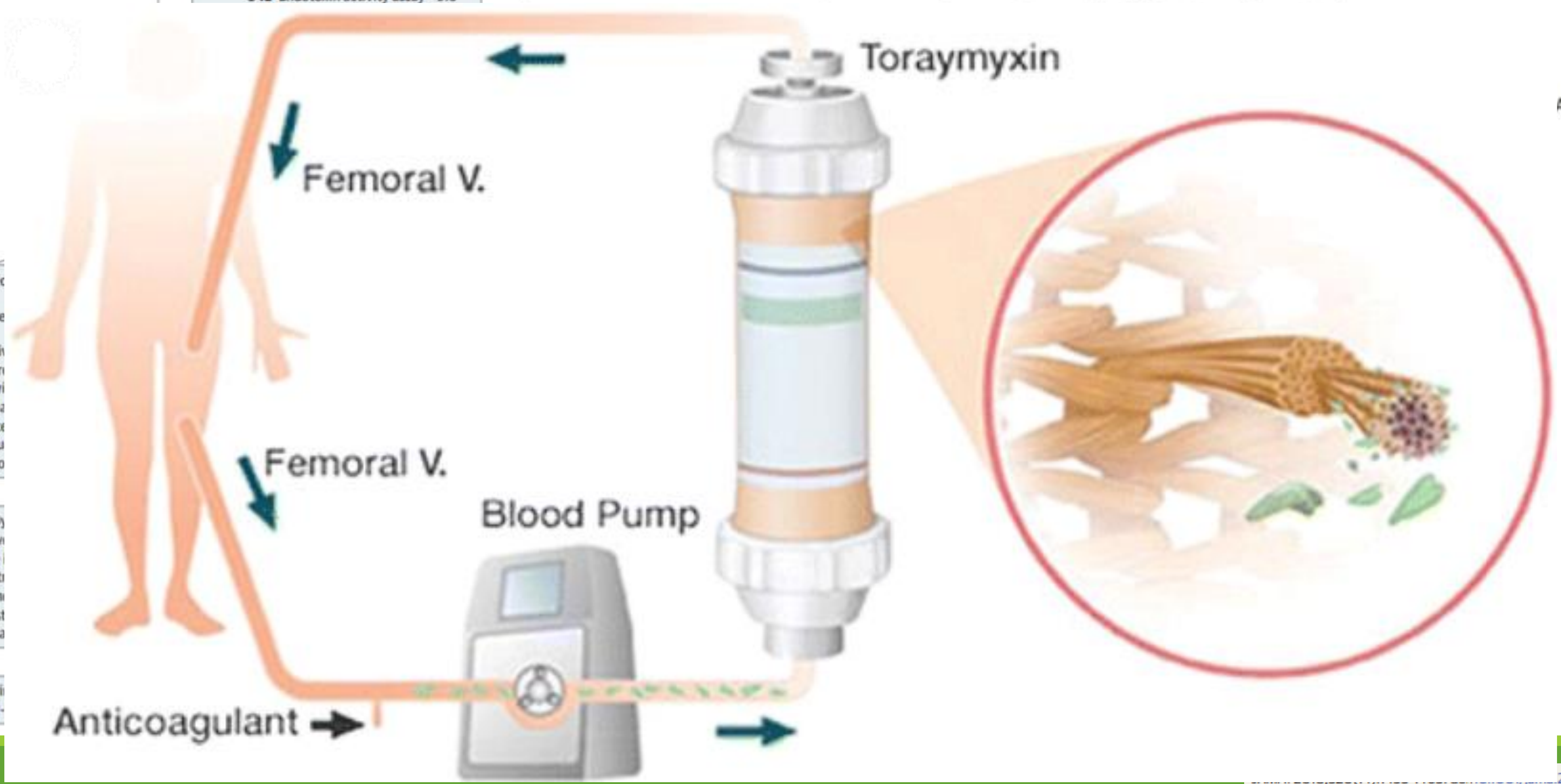
921 Patients screened for septic shock consented for endotoxin activity assay

471 Excluded
342 Endotoxin activity assay <0.6

224 Randomized to rec
hemoperfusion[a]
212 Received inte
randomized
12 Did not recei
5 Died befor
2 Consent wi
1 Dialysis ma
1 Lack of site
1 Lack of stu
2 Inability to

147 >9 Multiple Organ Dy
139 Received interv
8 Did not receive
3 Died before t
2 Consent with
1 Lack of site st
2 Inability to ca

146 Included in pri
1 Lost to follow-



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ORIGINAL

Polymyxin B hemoperfusion in endotoxemic septic shock patients without extreme endotoxemia: a post hoc analysis of the EUPHRATES trial

D. J. Klein[1*], D. Foster[2], P. M. Walker[2], S. M. Bagshaw[3], H. Mekonnen[4] and M. Antonelli[5]

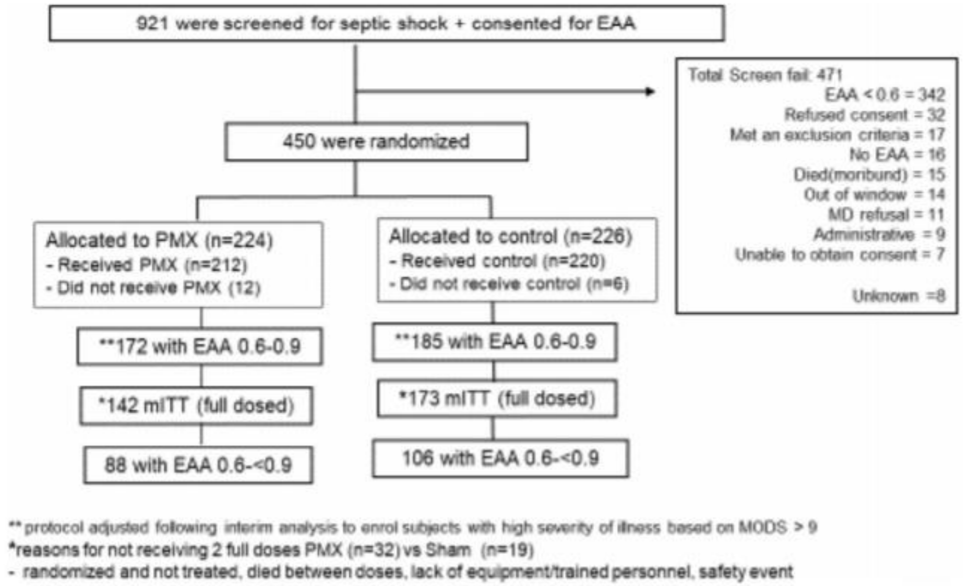


Fig. 1 Consort diagram

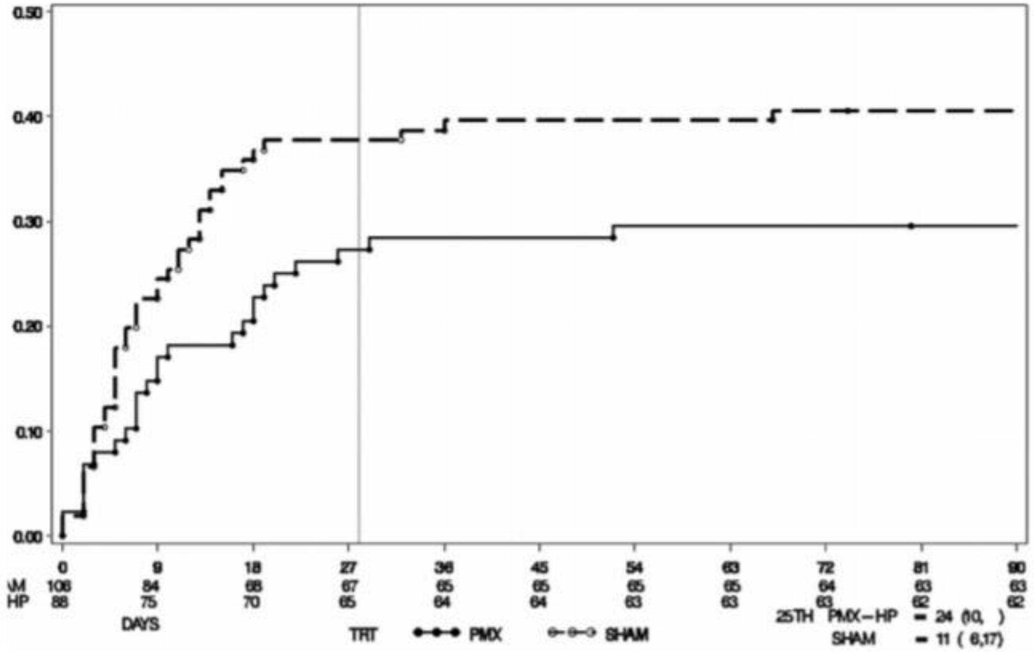


Fig. 2 Time to death within 90 days for PMX versus sham. Kaplan-Meier estimates of the probability of survival to day 90 among 194 per-protocol patients with MODS > 9 and EAA between 0.6 and 0.89, by treatment groups. The 90-day results of Cox proportional hazards adjusted for baseline MAP and APACHE II score are the hazard ratio [0.57, 95% CI (0.35, 0.93), *P* value = 0.02]. The vertical line represents the 28-day interval. The 28-day adjusted Cox proportional hazard ratio for death in the PMX group compared with the sham group is 0.58 (95% CI, 0.35 to 0.98; *P* = 0.04). *TRT* treatment, *25th* 25th percentile at 90 days

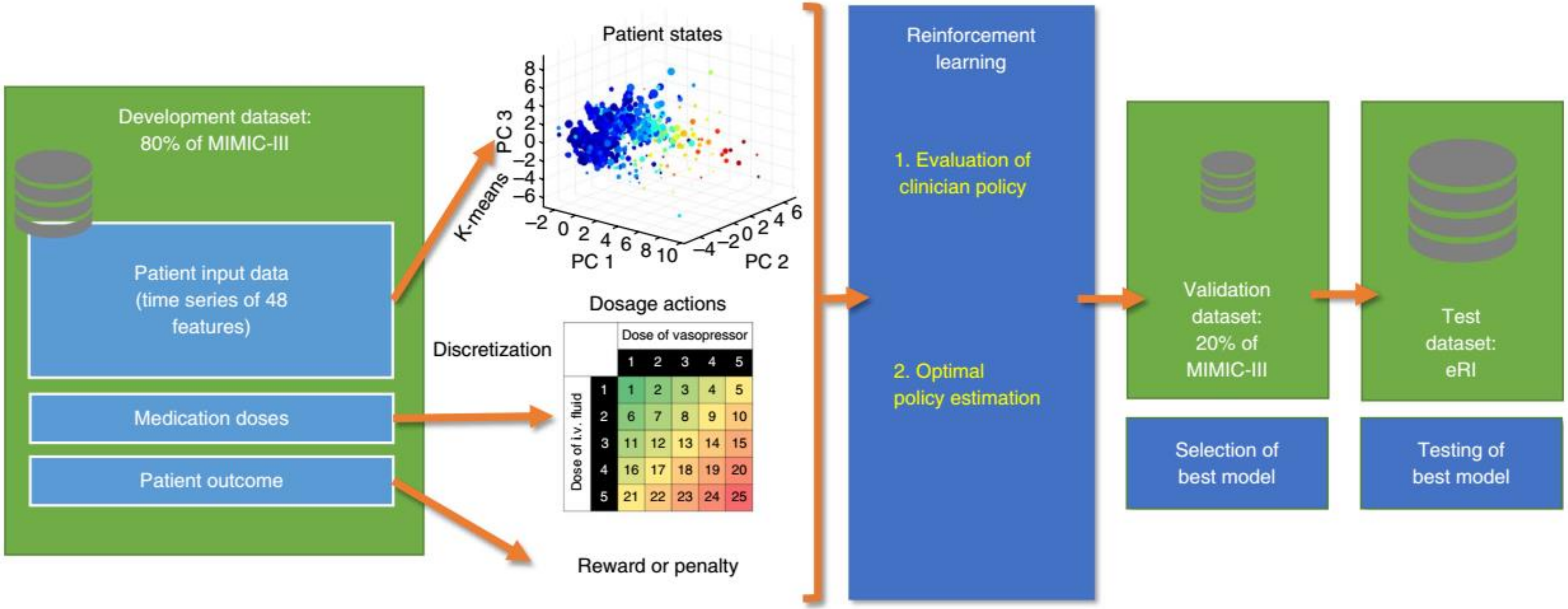
Intensive Care Med (2018) 44:2205–2212
https://doi.org/10.1007/s00134-018-5463-7


AIDE À LA DÉCISION
DIAGNOSTIQUE
ET THÉRAPEUTIQUE

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

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*]



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

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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*]

Sepsis is the third leading cause of death worldwide and the main cause of mortality in hospitals[1–3], but the best treatment strategy remains uncertain. In particular, evidence suggests that current practices in the administration of intravenous fluids and vasopressors are suboptimal and likely induce harm in a proportion of patients[1,4–6]. To tackle this sequential decision-making problem, we developed a reinforcement learning agent, the Artificial Intelligence (AI) Clinician, which extracted implicit knowledge from an amount of patient data that exceeds by many-fold the life-time experience of human clinicians and learned optimal treatment by analyzing a myriad of (mostly suboptimal) treatment decisions. We demonstrate that the value of the AI Clinician's selected treatment is on average reliably higher than human clinicians. In a large validation cohort independent of the training data, mortality was lowest in patients for whom clinicians' actual doses matched the AI decisions. Our model provides individualized and clinically interpretable treatment decisions for sepsis that could improve patient outcomes.

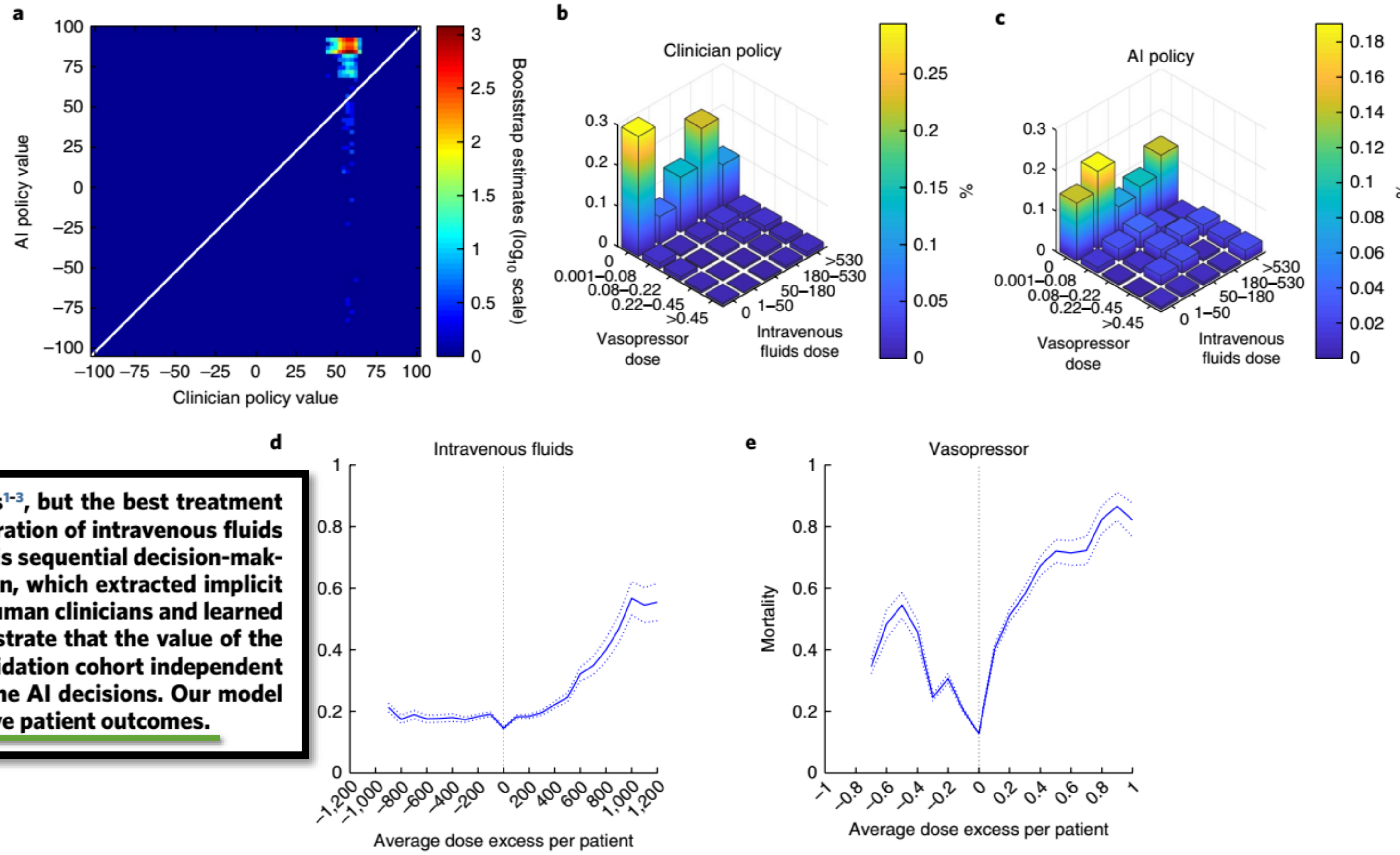


Fig. 3 | Comparison of clinician and AI policies in eRI and average dose excess received per patient of both drugs in eRI with corresponding mortality. a,

RESEARCH Open Access

Performance of closed-loop resuscitation of haemorrhagic shock with fluid alone or in combination with norepinephrine: an experimental study

Nicolas Libert[1,2], Guillaume Chenegros[3], Anatole Harrois[1,4], Nathalie Baudry[1], Gilles Cordurie[3], Ryad Benosman[3], Eric Vicaut[1,5] and Jacques Duranteau[1,4*]

Conclusions: This study assessed extensively the performances of several algorithms for closed-loop resuscitation of haemorrhagic shock with fluid alone and with co-administration of fluid and norepinephrine. The performance of the closed-loop algorithms tested was similar to physician-guided treatment with considerable saving of work for the caregiver. Arterial pressure closed-loop guided algorithms can be extended to combined administration of fluid and norepinephrine.

Fig. 2 Schematic of the system set-up. The CL-FNE combined a PI regulator for fluid and a FL regulator for NE. Several conditional rules were included to mimic the physician decisions. The algorithm needed three variables: systolic arterial pressure, systolic arterial pressure error and time. During resuscitation, it calculates the ratio of fluid volume/norepinephrine to adapt therapy

Abstract

Background: Closed-loop resuscitation can improve personalization of care, decrease workload and bring expert knowledge in isolated areas. We have developed a new device to control the administration of fluid or simultaneous co-administration of fluid and norepinephrine using arterial pressure.

Method: We evaluated the performance of our prototype in a rodent model of haemorrhagic shock. After haemor-

...than those resuscitated by a physician. Rats resuscitated with co-administration of fluid and norepinephrine required less fluid and had less hemodilution than rats resuscitated with fluid alone. Lactate decrease was similar between groups resuscitated with fluid alone and fluid with norepinephrine.

Conclusions: This study assessed extensively the performances of several algorithms for closed-loop resuscitation of haemorrhagic shock with fluid alone and with co-administration of fluid and norepinephrine. The performance of the closed-loop algorithms tested was similar to physician-guided treatment with considerable saving of work for the caregiver. Arterial pressure closed-loop guided algorithms can be extended to combined administration of fluid and norepinephrine.

Keywords: Closed-loop, Resuscitation, Haemorrhagic shock, Fluid, Norepinephrine

Libert *et al. Ann. Intensive Care* (2018) 8:89
https://doi.org/10.1186/s13613-018-0436-0

Annals of Intensive Care

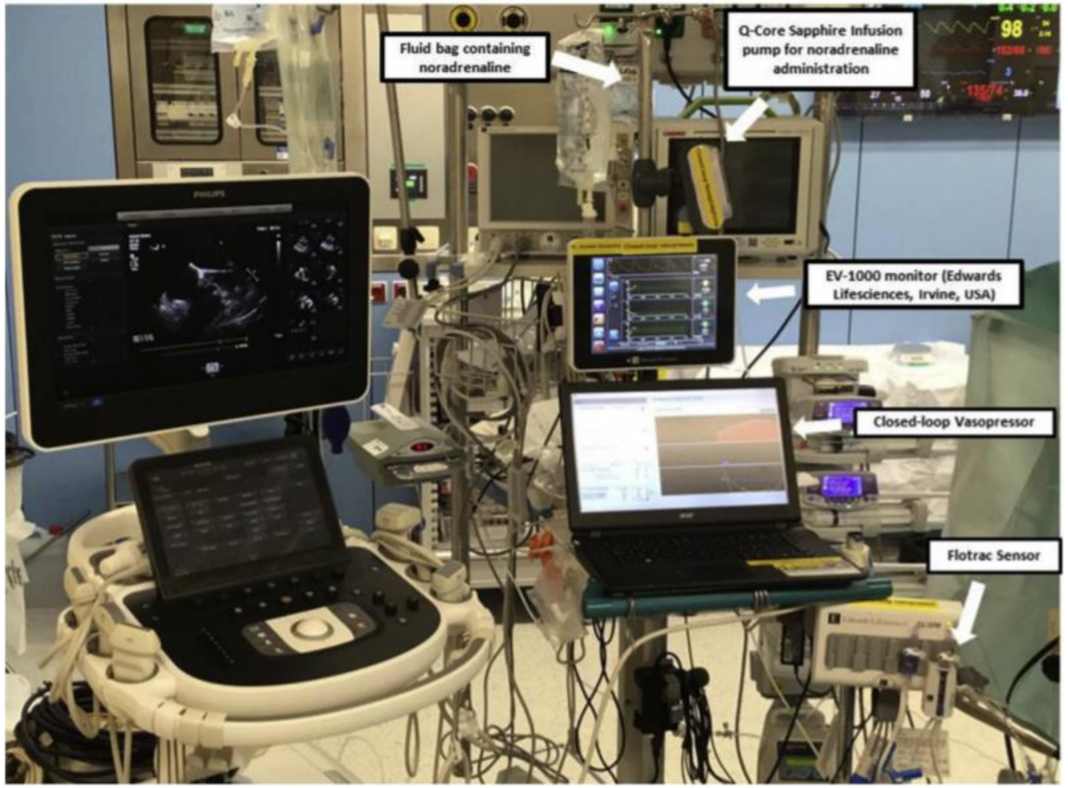
BJA British Journal of Anaesthesia, xxx (xxx): xxx (xxxx)

doi: 10.1016/j.bja.2019.04.064
Advance Access Publication Date: xxx
Clinical Investigation

CLINICAL INVESTIGATION

Feasibility of closed-loop titration of norepinephrine infusion in patients undergoing moderate- and high-risk surgery

Alexandre Joosten[1,2,*], Brenton Alexander[3], Jacques Duranteau[2], Fabio Silvio Taccone[4], Jacques Creteur[4], Jean-Louis Vincent[4], Maxime Cannesson[5] and Joseph Rinehart[6]



Abstract

Background: Vasopressor agents are used to prevent intraoperative hypotension and ensure adequate perfusion. Vasopressors are usually administered as intermittent boluses or manually adjusted infusions, but this practice requires considerable time and attention. We have developed a closed-loop vasopressor (CLV) controller to correct hypotension more efficiently. Here, we conducted a proof-of-concept study to assess the feasibility and performance of CLV control in surgical patients.

Methods: Twenty patients scheduled for elective surgical procedures were included in this study. The goal of the CLV system was to maintain MAP within 5 mm Hg of the target MAP by automatically adjusting the rate of a norepinephrine infusion using MAP values recorded continuously from an arterial catheter. The primary outcome was the percentage of time that patients were hypotensive, as defined by a MAP of 5 mm Hg below the chosen target. Secondary outcomes included the total dose of norepinephrine, percentage of time with hypertension (MAP>5 mm Hg of the chosen target), raw percentage "time in target" and Varvel performance criteria.

Results: The 20 subjects (median age: 64 years [52–71]; male (35%)) underwent elective surgery lasting 154 min [124–233]. CLV control maintained MAP within ±5 mm Hg of the target for 91.6% (85.6–93.3) of the intraoperative period. Subjects were hypotensive for 2.6% of the intraoperative period (range, 0–8.4%). Additional performance criteria for the controller included mean absolute performance error of 2.9 (0.8) and mean predictive error of 0.5 (1.0). No subjects experienced major complications.

Conclusions: In this proof of concept study, CLV control minimised perioperative hypotension in subjects undergoing moderate- or high-risk surgery. Further studies to demonstrate efficacy are warranted.

Trial registry number: NCT03515161 (ClinicalTrials.gov).

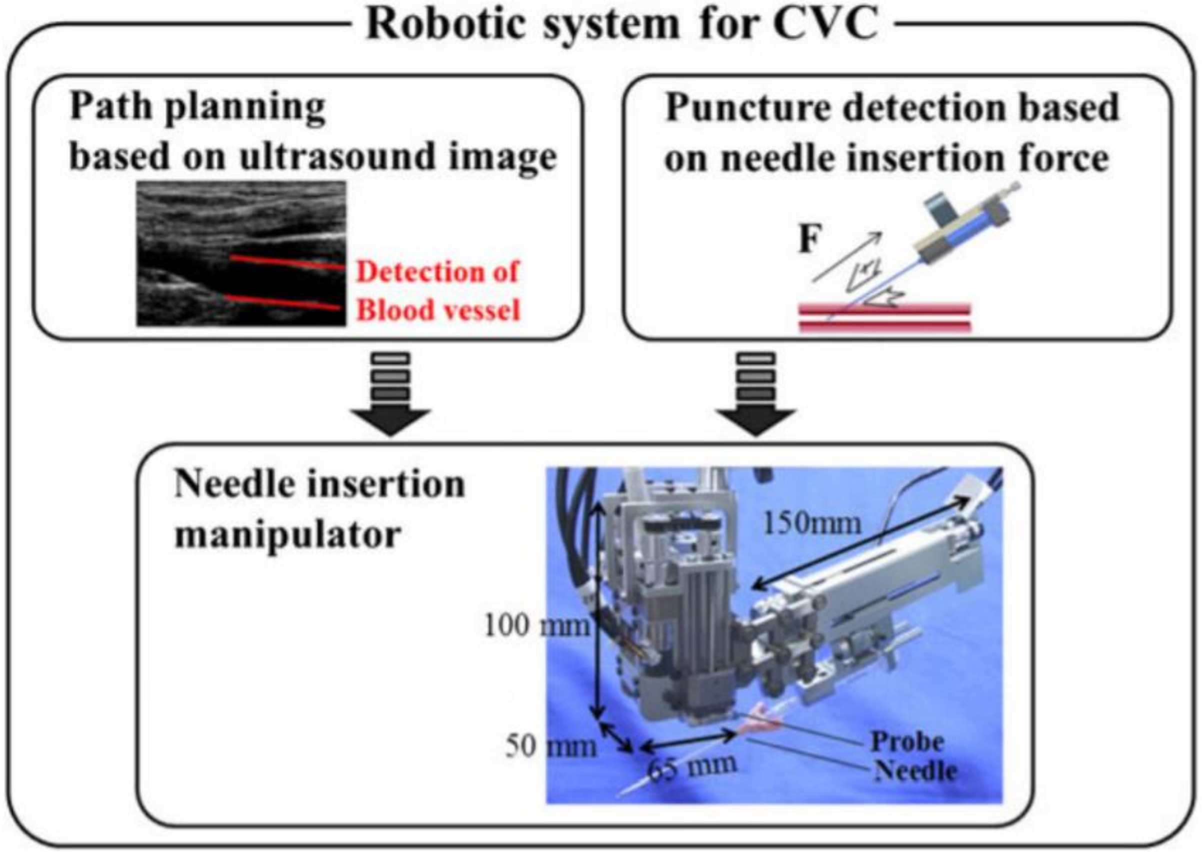

CHIRURGIE ASSISTÉE
PAR ORDINATEUR

The International Journal of **Medical Robotics** and **Computer Assisted Surgery**

THE INTERNATIONAL JOURNAL OF MEDICAL ROBOTICS AND COMPUTER ASSISTED SURGERY
Int J Med Robotics Comput Assist Surg 2012; **8**: 34–44.
Published online 24 October 2011 in Wiley Online Library (wileyonlinelibrary.com) **DOI:** 10.1002/rcs.420

ORIGINAL ARTICLE

Development of a needle insertion manipulator for central venous catheterization



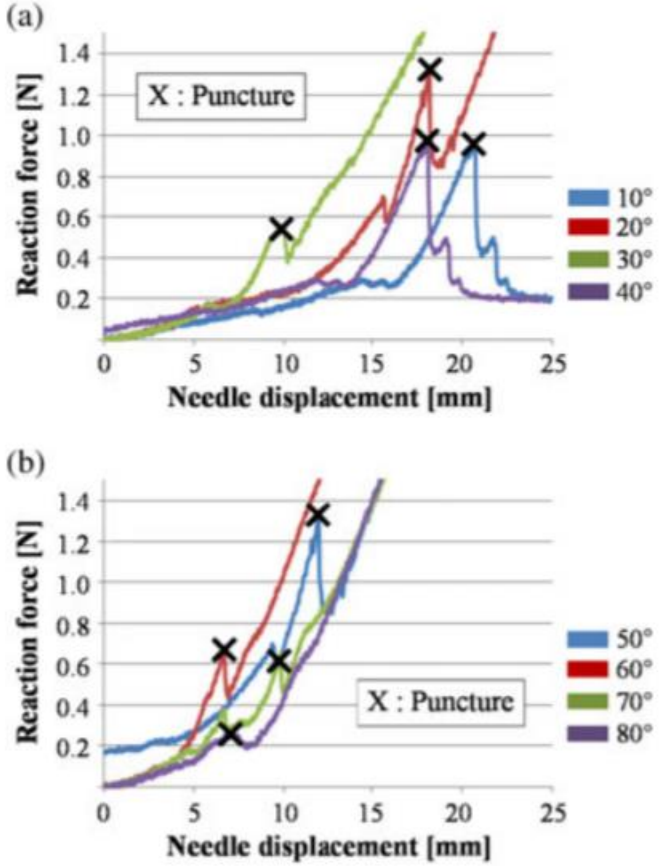
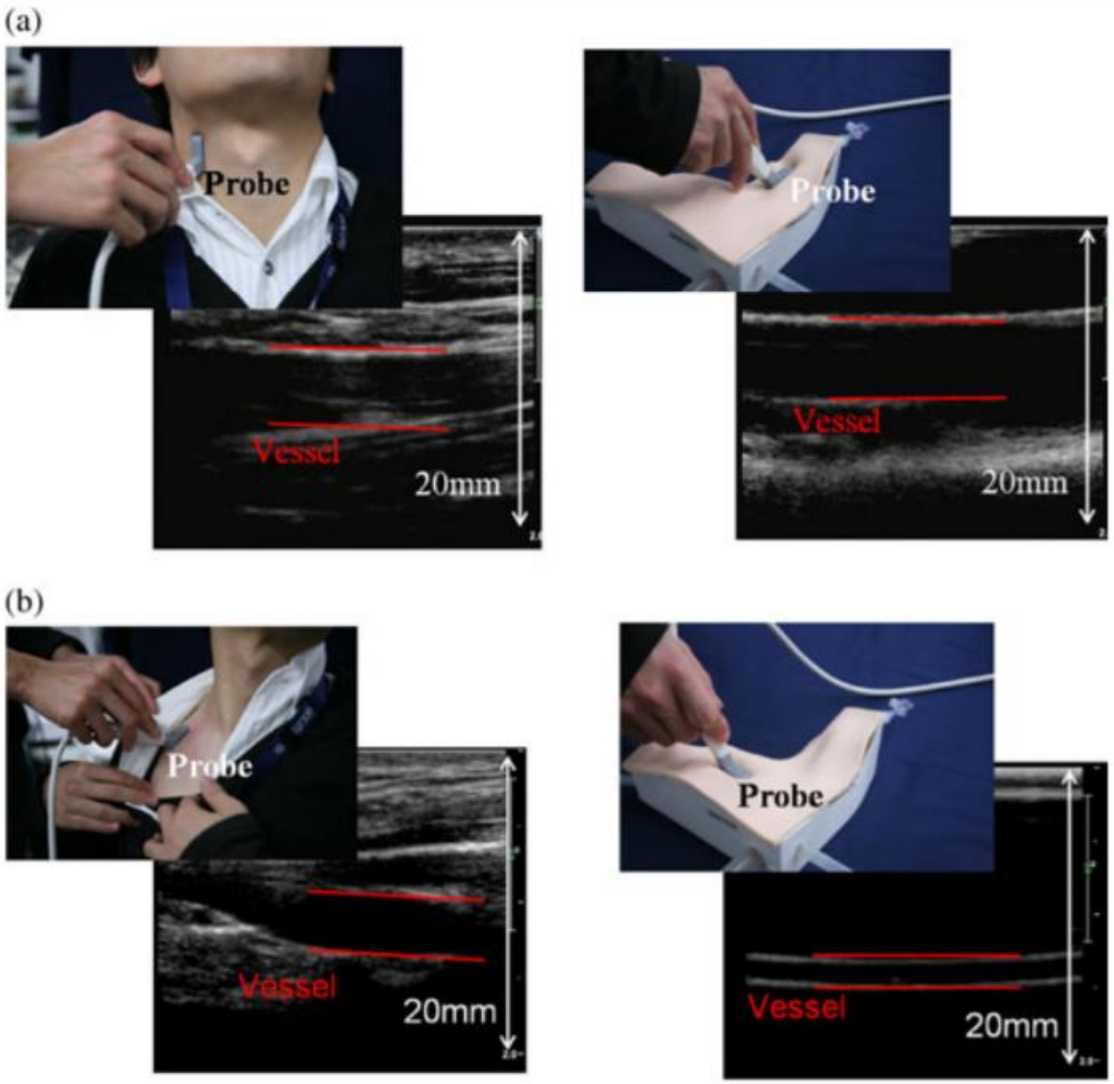


Figure 3. Experimental results showing needle insertion force: (a) 10–40°; (b) 50–80°


(a)
Probe
Vessel
20mm
Probe
Vessel
20mm
(b)
Probe
Vessel
20mm
Probe
Vessel
20mm

Vincent *Critical Care* 2017, **21**(Suppl 3):314
DOI 10.1186/s13054-017-1910-z
Critical Care
REVIEW Open Access

The coming era of precision medicine for intensive care

Jean-Louis Vincent

Conclusion

- Le sepsis est une pathologie qui met en jeu le pronostic vital
- Les traitements utilisés dans le sepsis ont peu évolué au cours 2 dernières décennies,
- L'intelligence artificielle est prometteuse et pourrait améliorer le diagnostic et le pronostic du sepsis


Training set
Training folds
Test fold
1st iteration
2nd iteration
3rd iteration
10th iteration
E_1
E_2
E_3
E_{10}
$E = \frac{1}{10}\sum_{i=1}^{10} E_i$