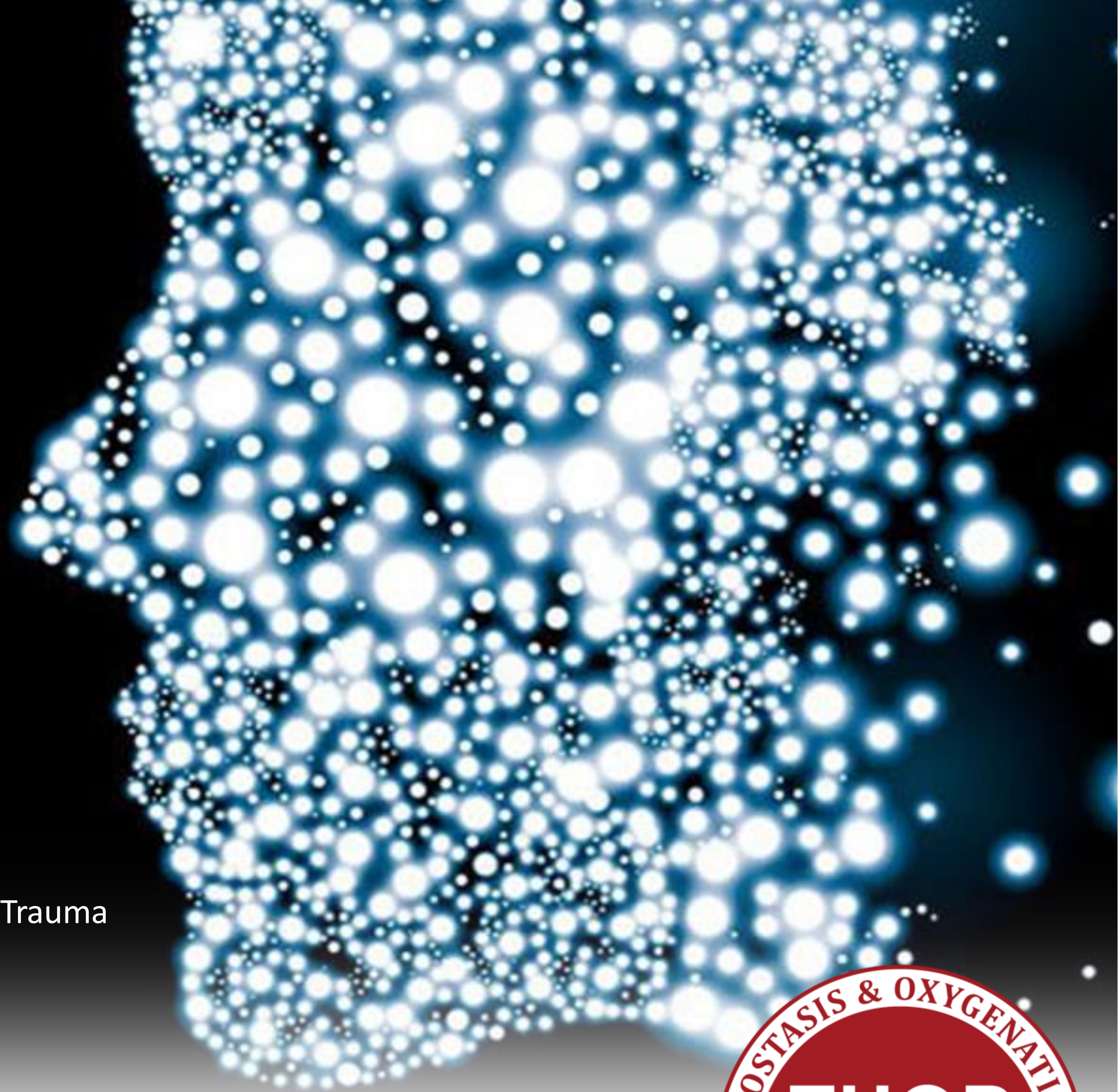
THOR Solstrand Hotel, Norway 19-21st May 2025

Artificial Intelligence: Bleeding



Max Marsden

Honorary Clinical Lecturer, Centre for Trauma Sciences, QMUL, UK

Senior Lecturer in Surgical Informatics, Academic Department of Military Surgery and Trauma

DMS Defence Medical Services | Centre for Trauma Sciences | London's Air Ambulance | Queen Mary University of London | Trauma Hemostasis & Oxygenation Research THOR

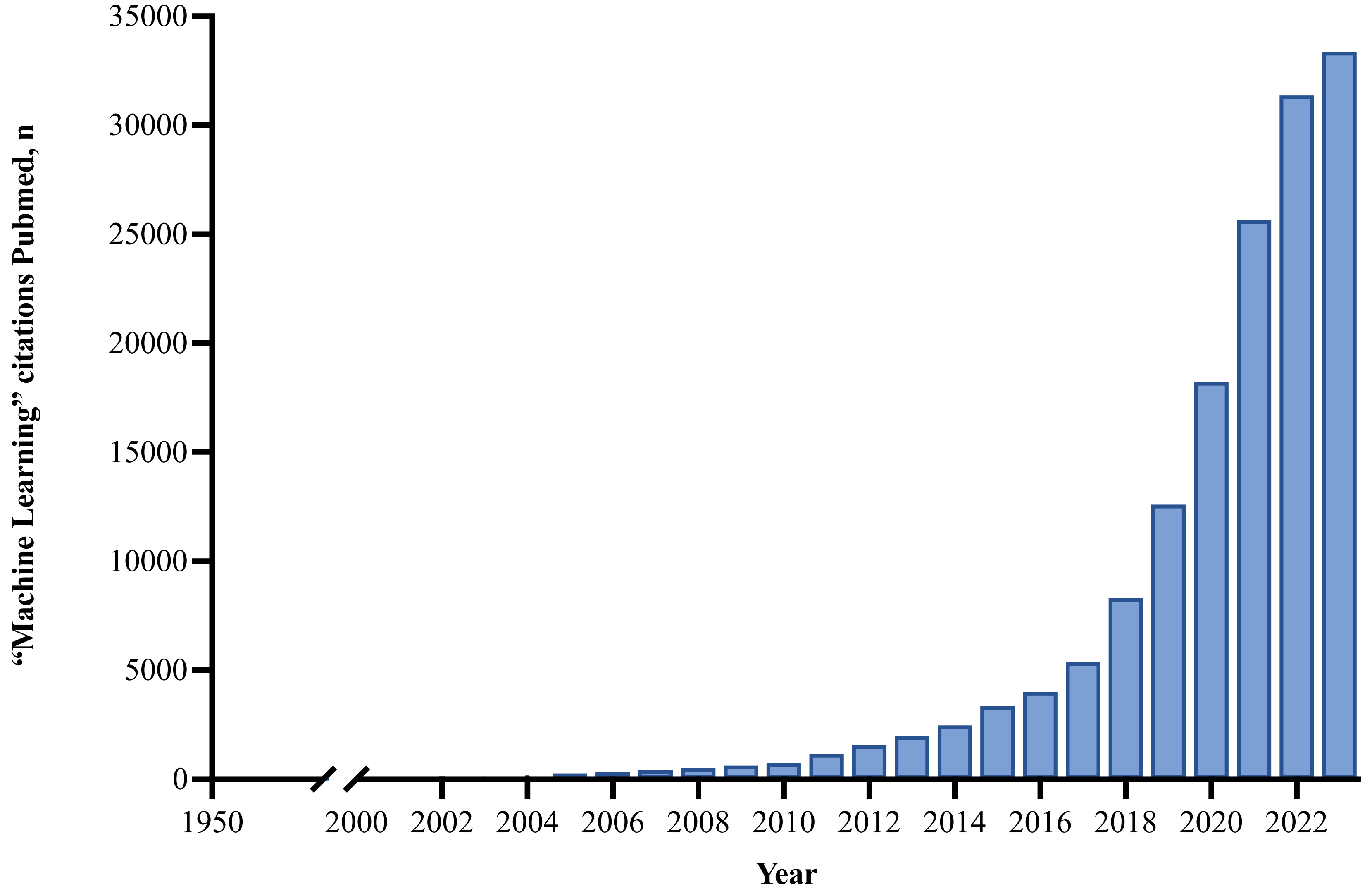

ISAF

Why now?

Caution

Modeling bleeding

Our Approach - Bayes



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"Machine Learning" citations Pubmed, n
1950
2000
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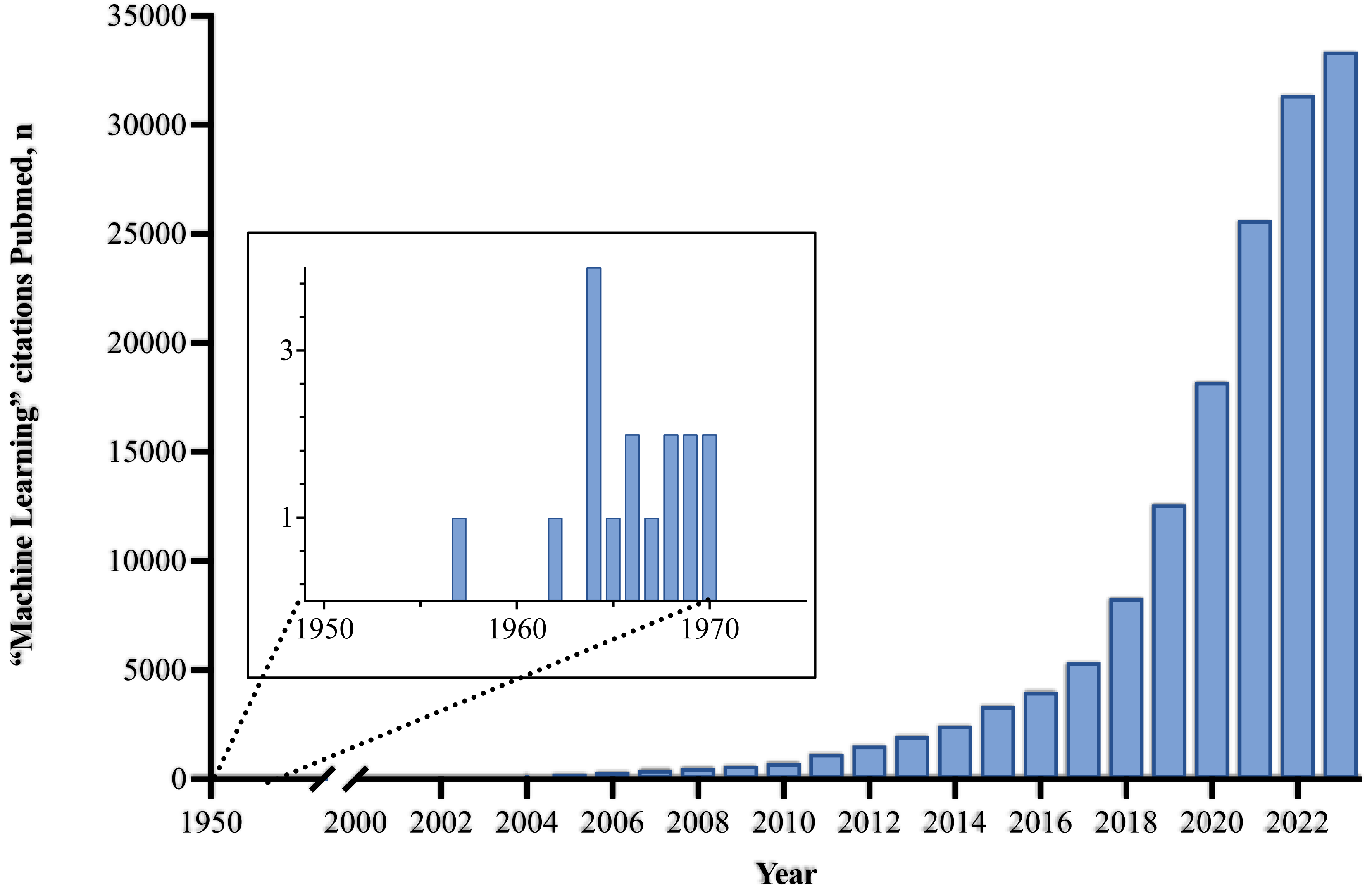
2022
Year



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"Machine Learning" citations Pubmed, n
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2006
2008
2010
2012
2014
2016
2018
2020
2022
Year
3
1
1950
1960
1970

VOL. LIX. No. 236.] [October, 1950

MIND

A QUARTERLY REVIEW OF PSYCHOLOGY AND PHILOSOPHY

I.—COMPUTING MACHINERY AND INTELLIGENCE

BY A. M. TURING

1. *The Imitation Game.*

I PROPOSE to consider the question, 'Can machines think ?' This should begin with definitions of the meaning of the terms 'machine' and 'think'. The definitions might be framed so as to reflect so far as possible the normal use of the words, but this attitude is dangerous. If the meaning of the words 'machine' and 'think' are to be found by examining how they are commonly used it is difficult to escape the conclusion that the meaning and the answer to the question, 'Can machines think ?' is to be sought in a statistical survey such as a Gallup poll. But this is absurd. Instead of attempting such a definition I shall replace the question by another, which is closely related to it and is expressed in relatively unambiguous words.

Workflow Enhancements	Diagnostics (e.g. image processing)	Decision Support	Predictive Analytics
Triage	Telemedicine	Robotics and Surgical Navigation	Monitoring & Alarms
Rehabilitation (wearables)	Psychological Aftercare	Research	Simulation & Training

Current knowledge and availability of machine learning across the spectrum of trauma science

Tobias Gauss[a], Zane Perkins[b] and Thorsten Tjardes[c]

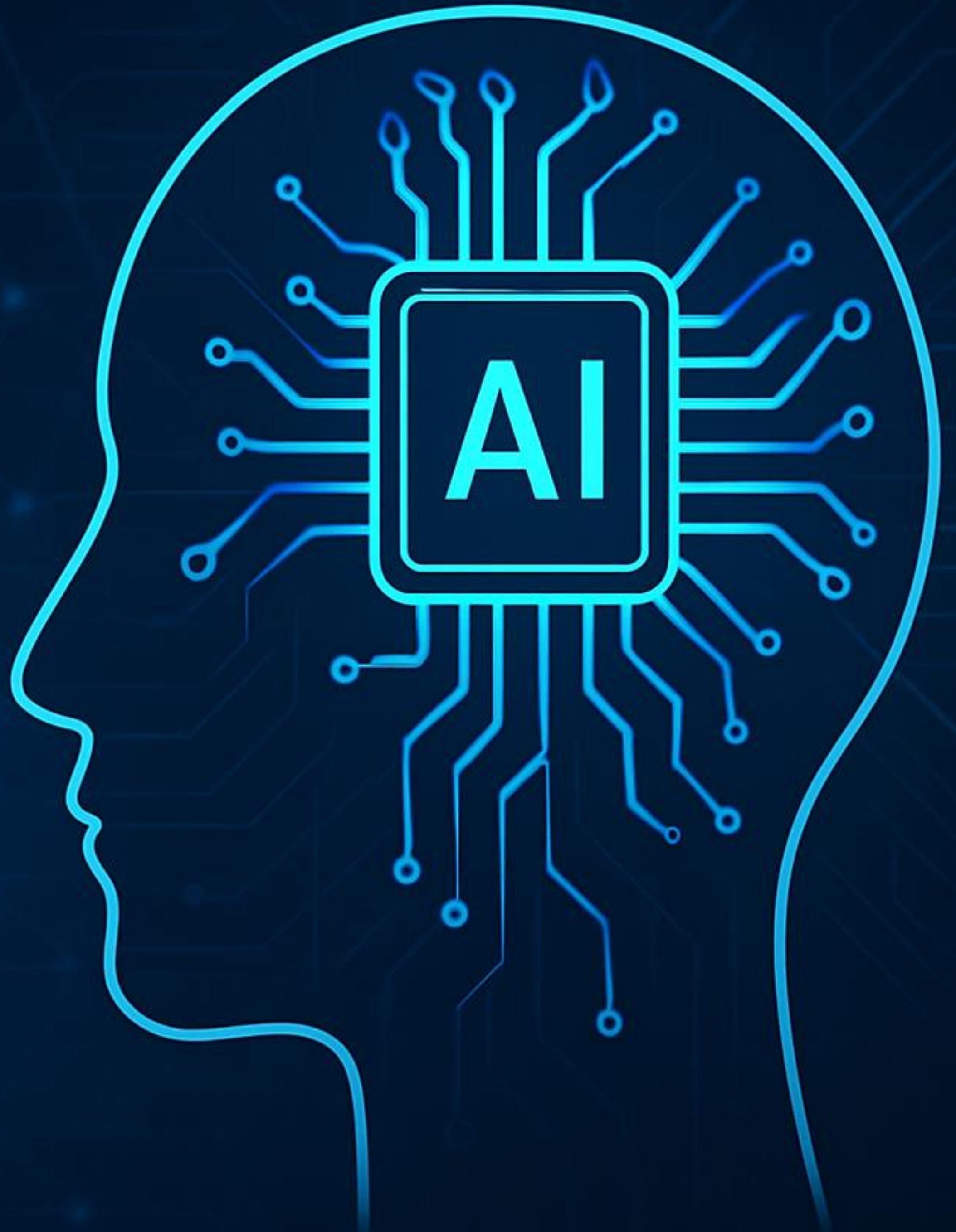
CURRENT OPINION

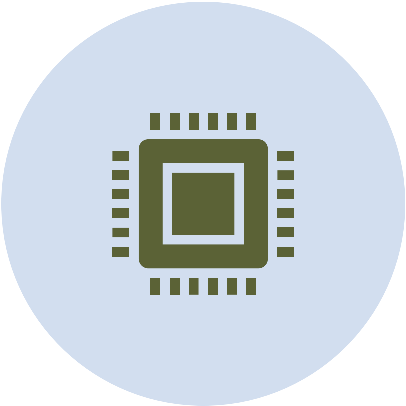
Current knowledge and availability of mach learning across the spectrum of trauma sc

Tobias Gauss[a], Zane Perkins[b] and Thorsten Tjardes[c]

Study dataset (*n* derivation set)	Objective	Algorithm type	Features	Output
Maurer *et al.* [25■] ACS-TQIP database (*n* = 934 053)	Smartphone-based mortality predictor tool	Optimal Classification Trees	sBP, HR, SpO_2, RR, GCS, temperature, AIS, mechanism, comorbidities, demographics,	Mortality, organ failure, complications
Lee *et al.* [26] Hospital data (*n* = 2232)	7-day mortality	XG Boost	Age, HR, RR, MAP, GCS, AIS, ED interventions	7-day mortality
Nederpelt *et al.* [27] ACS-TQIP database (*n* = 29 816)	In-field triage tool for need of critical resources	Deep Neural Network	Age, BMI, HR, SBP, RR, Temperature, GCS, AIS	Shock, massive transfusion (MT), major surgery
Follin *et al.* [28] Traumabase registry (*n* = 1160)	Need for critical resources	Decision tree	Age, HR, SpO_2, SBP, GCS, ISS, mechanism	Critical interventions and resources
Liu *et al.* [29] Trial data (*n* = 79)	Predict the need for lifesaving interventions in	Logistic regression (LR), Multilayer perceptron (MLP)	GCS, HR complexity, HR variability, shock index, pulse pressure, dBP, sBP, HR, SpO_2	Life-saving intervention
Perkins *et al.* [18■] Hospital data (*n* = 1091)	Prediction coagulopathy, critical interventions, massive transfusion	Bayes network	HR, SBP, temperature, hemothorax, FAST, GCS, lactate, pH, mechanism, fractures	Coagulopathy, critical intervention, LOS ICU
Moyer *et al.* [30] Traumabase registry (*n* = 2159)	Need for emergency neurosurgery	Logistic regression, Cat Boost	Prehospital physiological parameters and interventions	Need for emergency neurosurgery

WHY NOW?



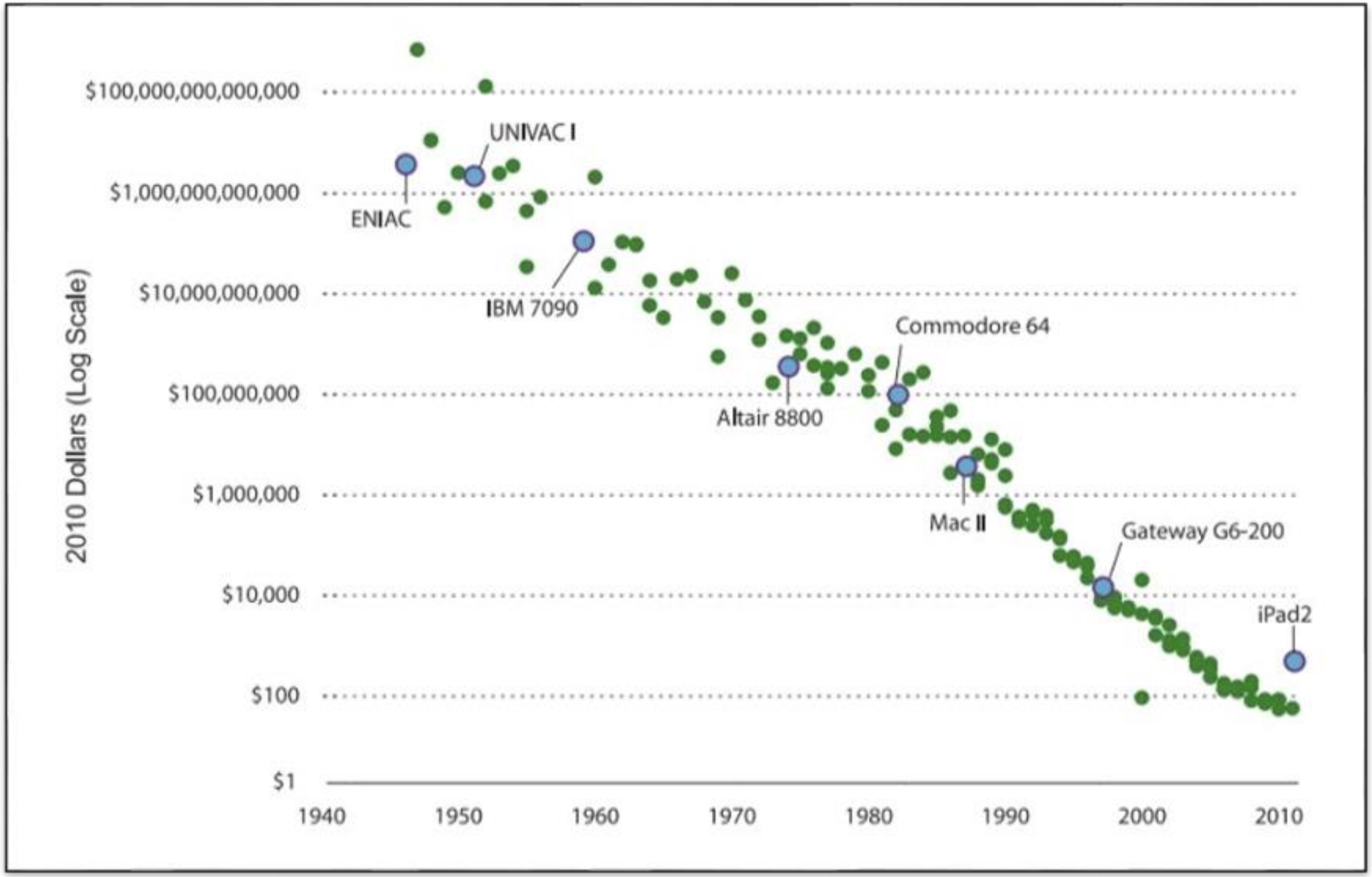


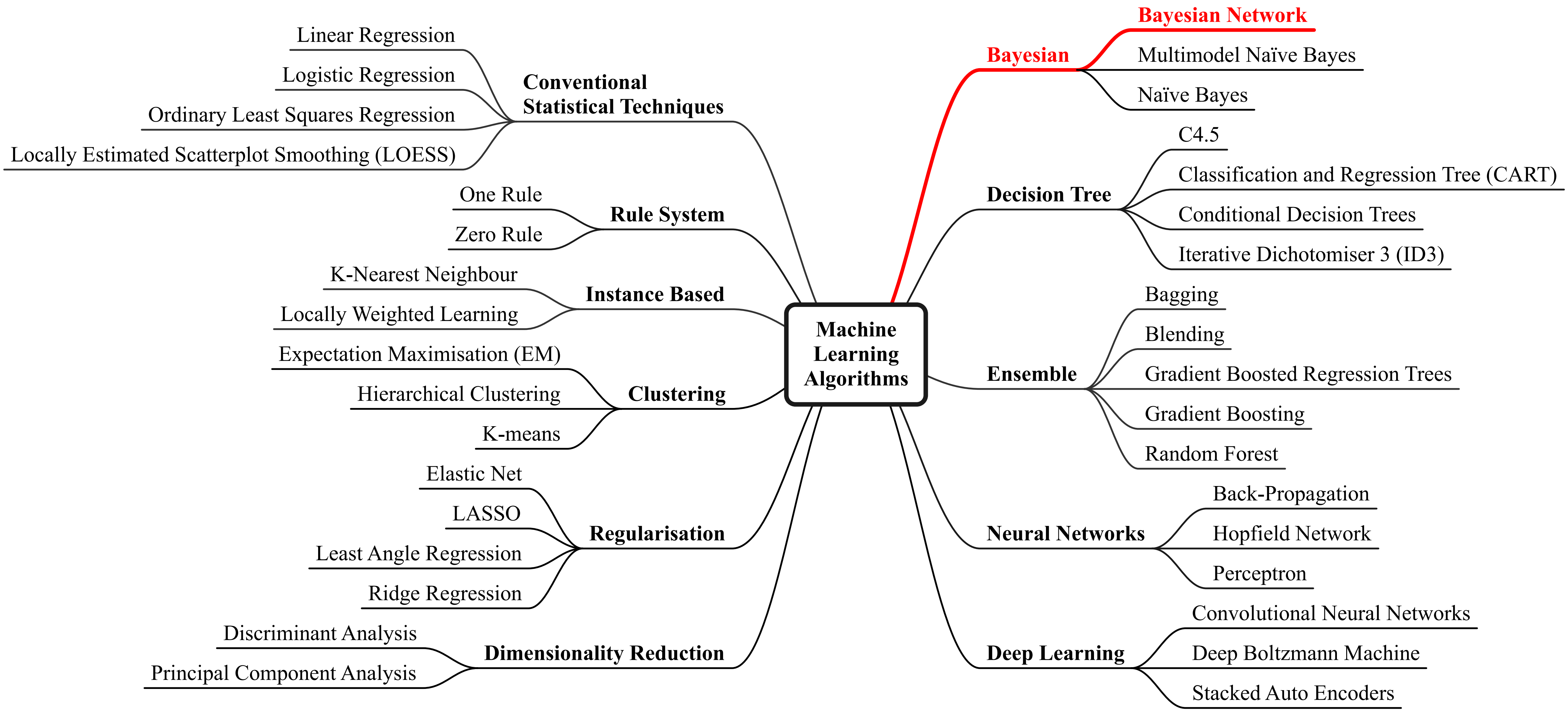
Compute

Data

Funding

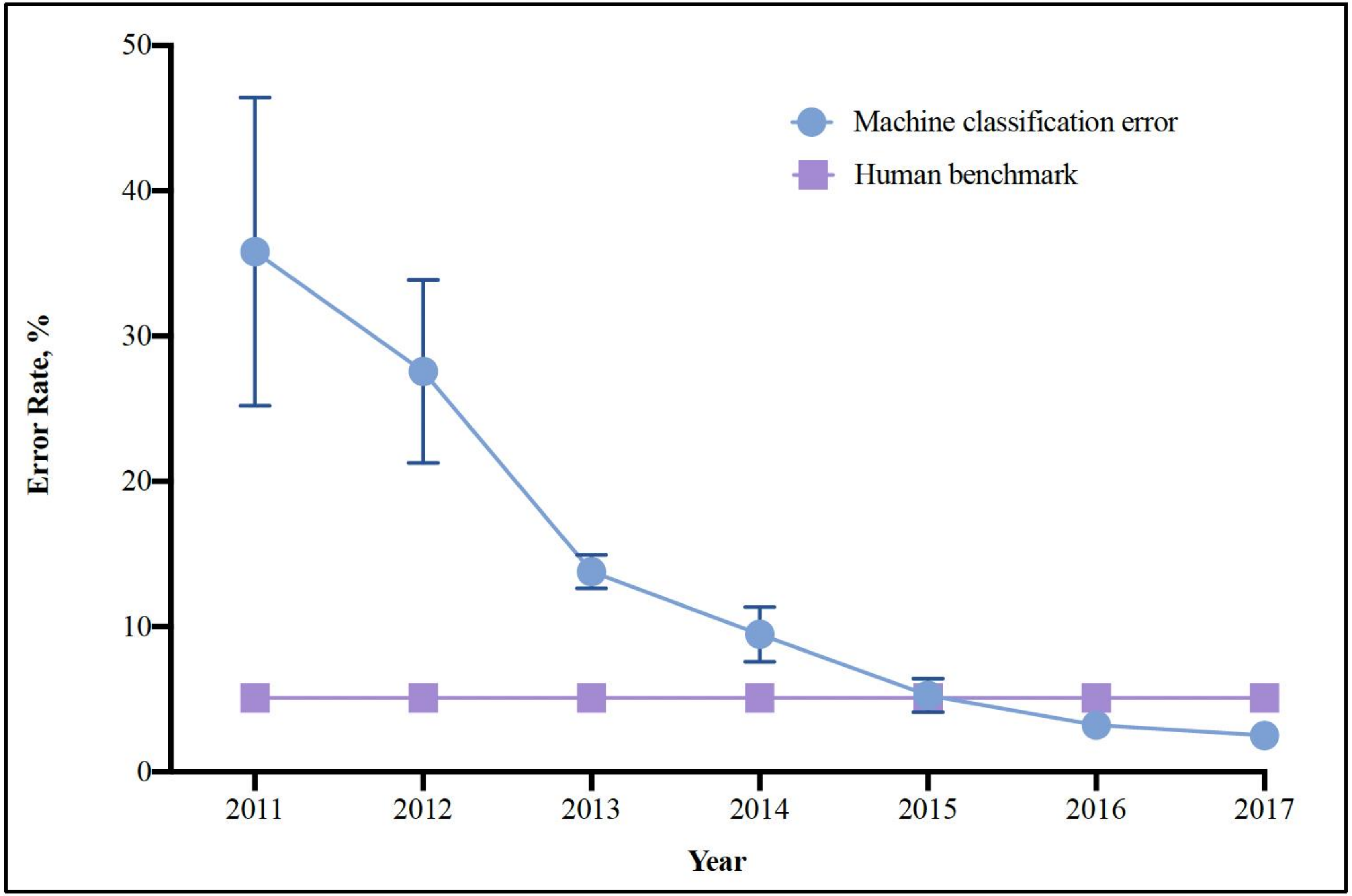
Cost of iPad 2 equivalent computing




Machine Learning Algorithms
Conventional Statistical Techniques
Linear Regression
Logistic Regression
Ordinary Least Squares Regression
Locally Estimated Scatterplot Smoothing (LOESS)
Rule System
One Rule
Zero Rule
Instance Based
K-Nearest Neighbour
Locally Weighted Learning
Clustering
Expectation Maximisation (EM)
Hierarchical Clustering
K-means
Regularisation
Elastic Net
LASSO
Least Angle Regression
Ridge Regression
Dimensionality Reduction
Discriminant Analysis
Principal Component Analysis
Bayesian
Bayesian Network
Multimodel Naïve Bayes
Naïve Bayes
Decision Tree
C4.5
Classification and Regression Tree (CART)
Conditional Decision Trees
Iterative Dichotomiser 3 (ID3)
Ensemble
Bagging
Blending
Gradient Boosted Regression Trees
Gradient Boosting
Random Forest
Neural Networks
Back-Propagation
Hopfield Network
Perceptron
Deep Learning
Convolutional Neural Networks
Deep Boltzmann Machine
Stacked Auto Encoders

Error rate of image classification

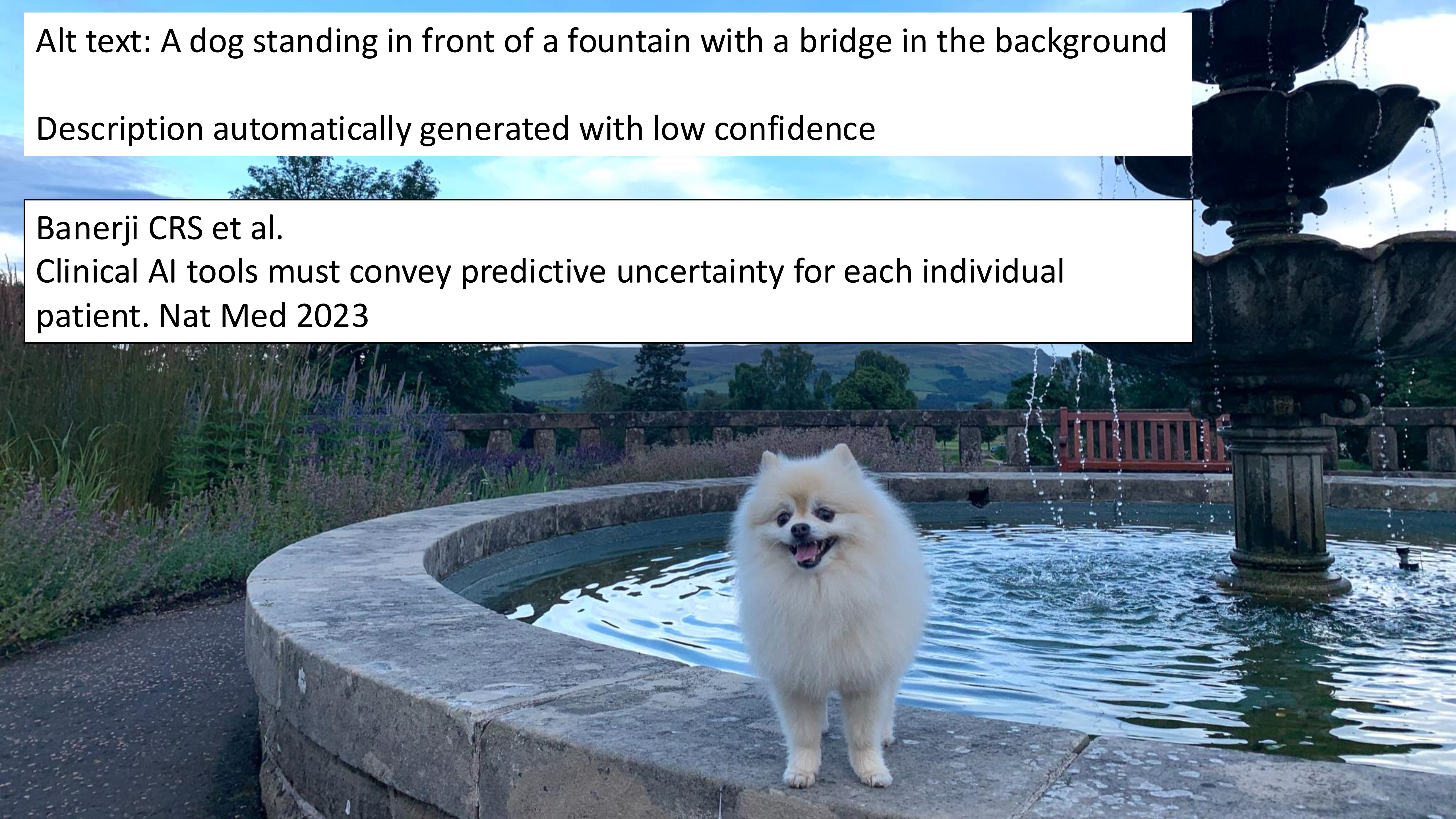
ImageNet challenge

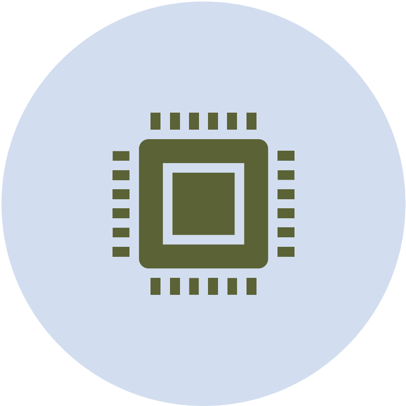


Alt text: A dog standing in front of a fountain with a bridge in the background

Description automatically generated with low confidence

Banerji CRS et al.
Clinical AI tools must convey predictive uncertainty for each individual patient. Nat Med 2023





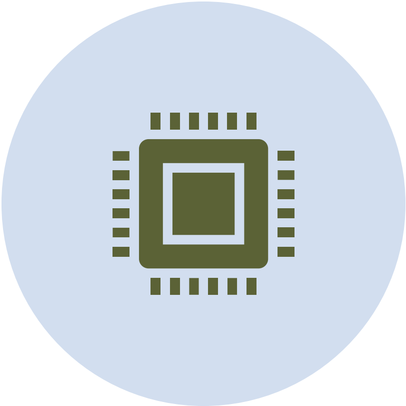
Compute

Data

Funding

"when you go from 10,000 training examples to 10 billion training examples, it all starts to work. Data trumps everything."

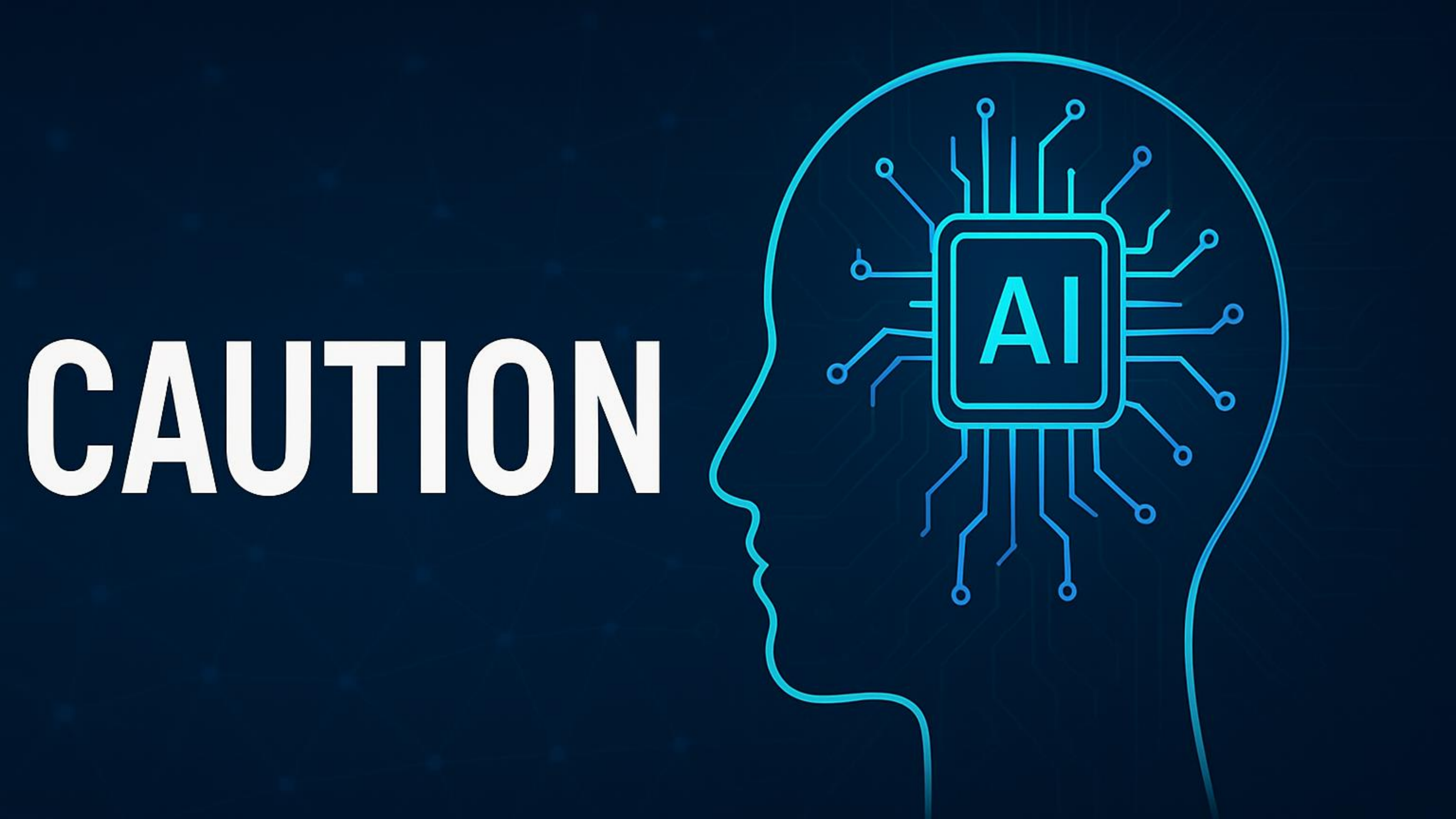
Google translate engineer



Compute

Data

Funding


CAUTION
AI

bmjmedicine

Check for updates

How to read a paper involving artificial intelligence (AI)

Paul Dijkstra ,[1] Trisha Greenhalgh ,[2] Yosra Magdi Mekki,[3] Jessica Morley[4]

[1]Nuffield Department of Orthopaedics, Rheumatology, and Musculoskeletal Sciences, University of Oxford, Oxford, UK
[2]Nuffield Department of Primary Care Health Sciences, University of Oxford, Oxford, UK
[3]Qatar University College of Medicine, Doha, Qatar
[4]Yale University, New Haven, Connecticut, USA

Correspondence to: Professor Trisha Greenhalgh, Nuffield Department of Primary Care Health Sciences, University of Oxford, Oxford, UK; trish.greenhalgh@phc.ox.ac.uk

Cite this as: *BMJMED* 2025;4. doi:10.1136/bmjmed-2025-001394

Received: 4 February 2025
Accepted: 19 March 2025

ABSTRACT

This paper guides readers through the critical appraisal of a paper that includes the use of artificial intelligence (AI) in clinical settings for healthcare delivery. A brief introduction to the different types of AI used in healthcare is given, along with some ethical principles to guide the introduction of AI systems into healthcare. Existing publication guidelines for AI studies are highlighted. Ten preliminary questions to ask about a paper describing an AI based decision support algorithm are suggested.

Introduction

Increasingly, clinical research papers describe the use of artificial intelligence (AI), and much has been written about the potential of AI to revolutionise healthcare.[1] Many examples exist of AI being rolled out into healthcare delivery (examples in boxes 1 and 2, and recent systematic reviews[2 3]), from the use of a machine learning algorithm to distinguish between a cough caused by a pulmonary tuberculosis[4] and non-tuberculosis respiratory condition (box 1) to using generative AI to improve deci-

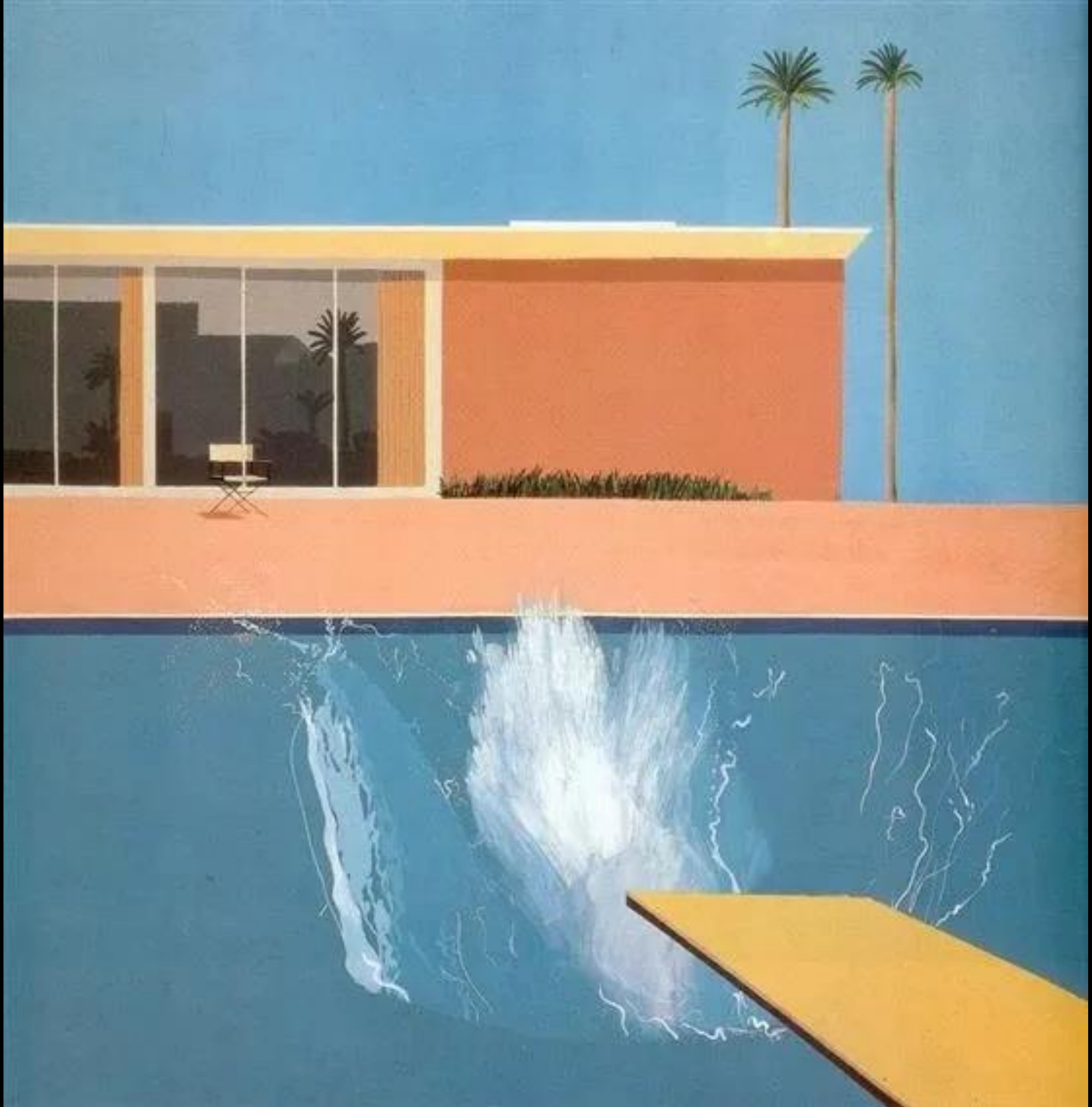
critical appraisal for papers that do not include the study of AI in clinical care.[5]

What is artificial intelligence?

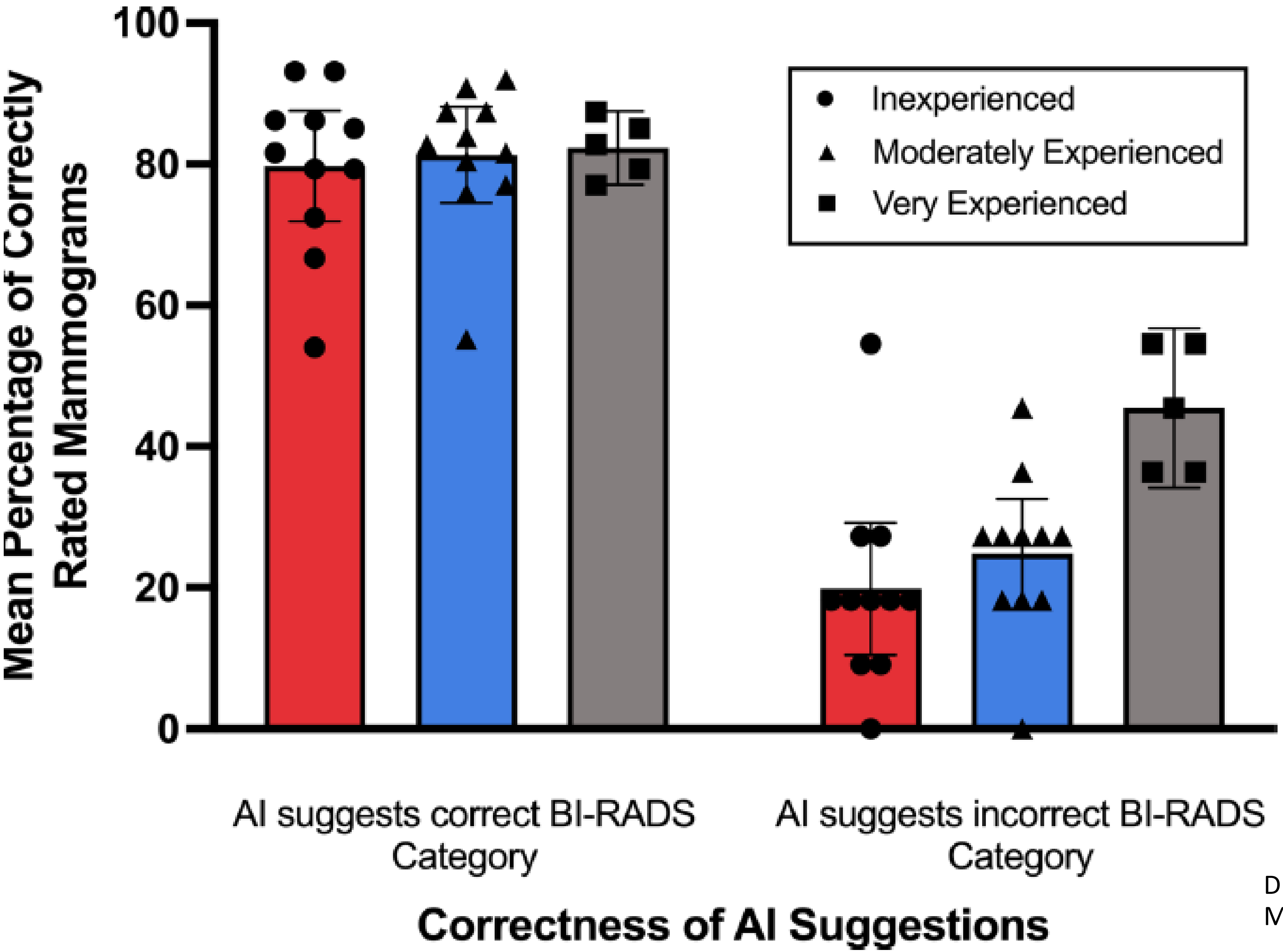
AI is a transformative technology capable of completing tasks that typically require human intelligence. AI is also an interdisciplinary area of research that spans, among other disciplines, computer science, psychology, linguistics, and philosophy. AI in healthcare is divided into two broad categories:

- Artificial narrow intelligence refers to machine learning algorithms that can recognise patterns in large datasets. Artificial narrow intelligence is useful for solving text, voice, or image based classification and clustering problems, excelling at a precisely defined, single task (eg, playing chess).
- Artificial general intelligence refers to AI applications that can reason, argue, memorise, and solve problems. Artificial general intelligence is sometimes referred to as human level AI, because it is considered to display a cognitive capacity which approximates to that of a human being.

Whereas artificial narrow intelligence is already

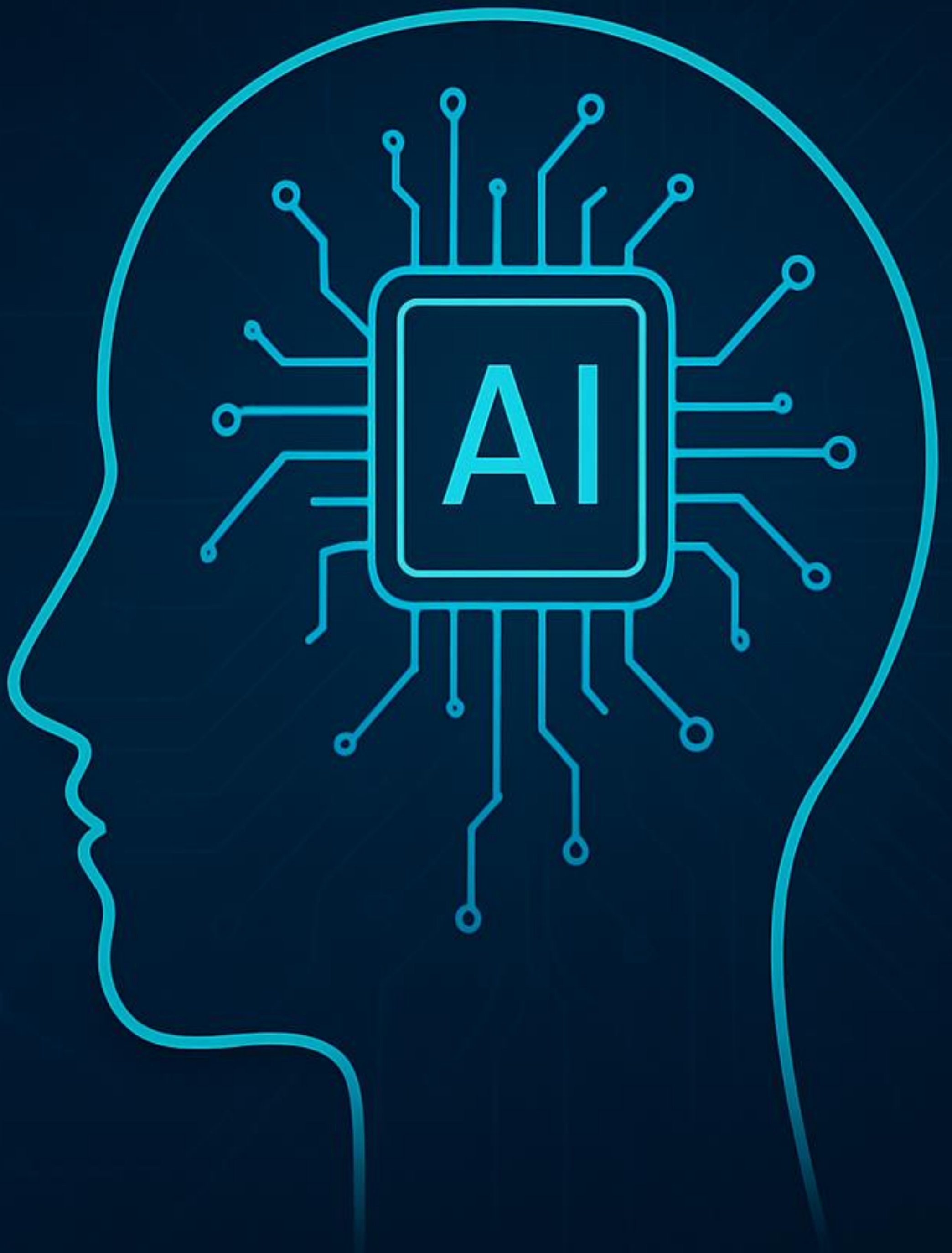


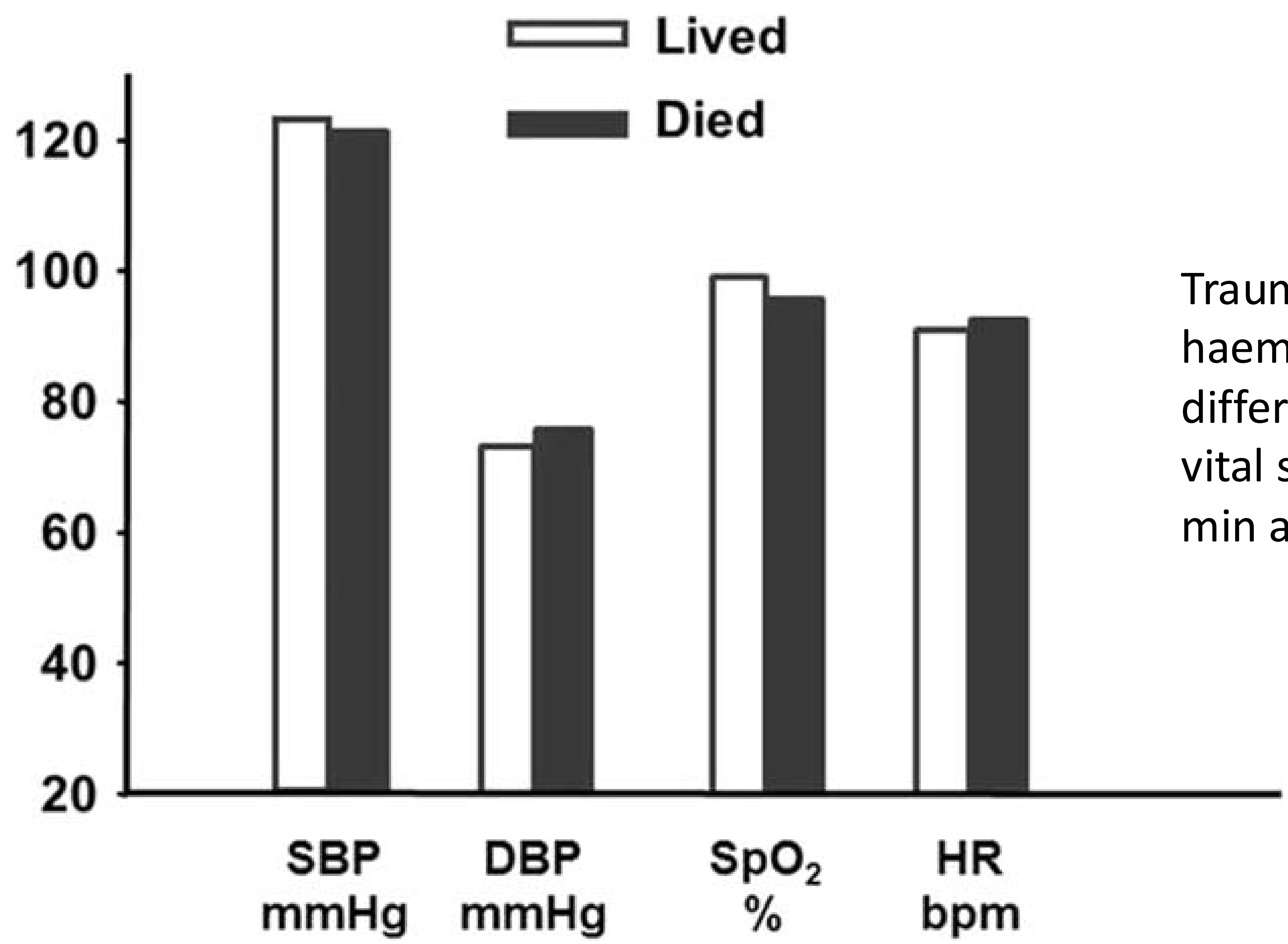
Human Machine Pairing



Dratsch, Automation Bias in Mammography *Radiology,* 2023

Blood prediction





Trauma patients with severe haemorrhage **could not** be differentiated by standard vital signs obtained 30 to 45 min after injury

Injury, Int. J. Care Injured 46 (2015) 807–813

Contents lists available at ScienceDirect

Injury

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

Clinical gestalt and the prediction of massive transfusion after trauma☆

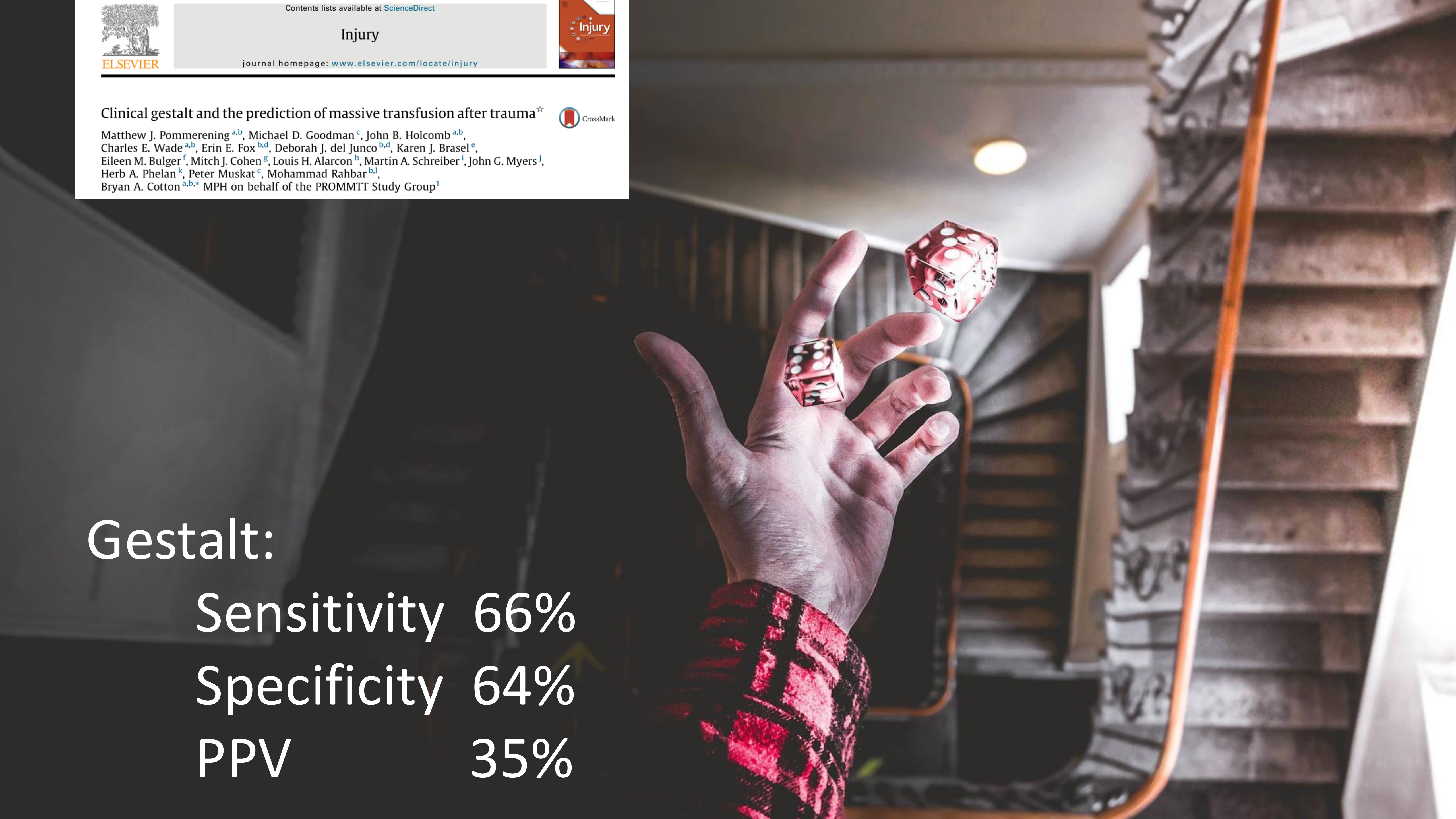
Matthew J. Pommerening[a,b], Michael D. Goodman[c], John B. Holcomb[a,b], Charles E. Wade[a,b], Erin E. Fox[b,d], Deborah J. del Junco[b,d], Karen J. Brasel[e], Eileen M. Bulger[f], Mitch J. Cohen[g], Louis H. Alarcon[h], Martin A. Schreiber[i], John G. Myers[j], Herb A. Phelan[k], Peter Muskat[c], Mohammad Rahbar[b,l], Bryan A. Cotton[a,b,*] MPH on behalf of the PROMMTT Study Group[1]

"Is the patient likely to be massively transfused?"

All patients received >1 unit of blood

966 patients

23% had a MT



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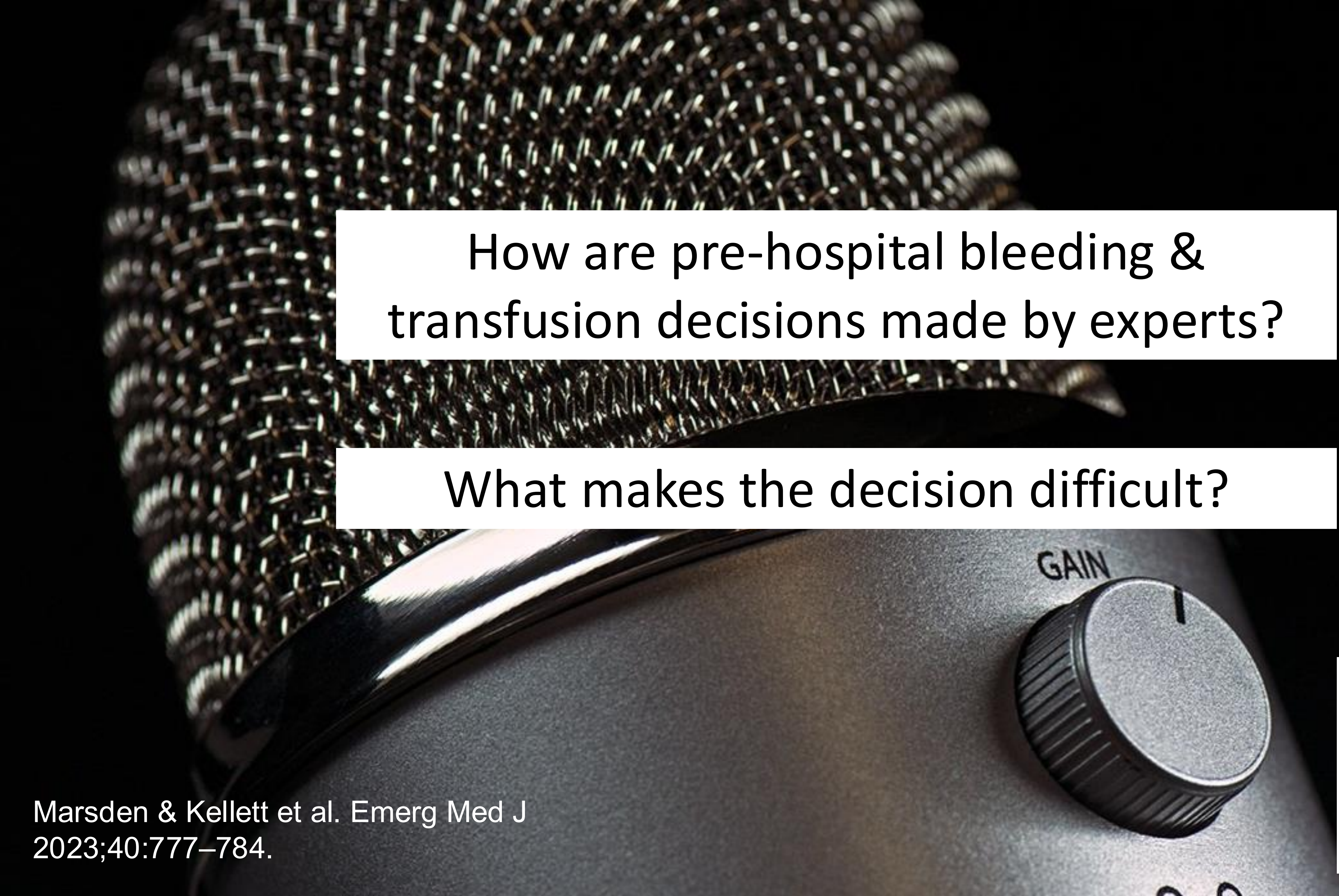
Gestalt:

Sensitivity	66%
Specificity	64%
PPV	35%

How are pre-hospital bleeding & transfusion decisions made by experts?

What makes the decision difficult?



Qualitative

Marsden & Kellett et al. Emerg Med J 2023;40:777–784.

Open access Original research

Trauma Surgery & Acute Care Open

Identification of major hemorrhage in trauma patients in the prehospital setting: diagnostic accuracy and impact on outcome

Jared M Wohlgemut[1,2] Erhan Pisirir[3] Rebecca S Stoner[1,2] Evangelia Kyrimi,[3] Michael Christian,[4] Thomas Hurst,[4] William Marsh[3] Zane B Perkins[1,2] Nigel R M Tai[1,2]

Quantitative

Open access Original research

Trauma Surgery & Acute Care Open

Identification of major hemorrhage in trauma patients in the prehospital setting: diagnostic accuracy and impact on outcome

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Accuracy of MHPA Sens 70%, Spec 94%

Mortality associated with missed Major Haemorrhage **OR 3.3**


Traditional
AI / ML

Traditional Modelling Approaches

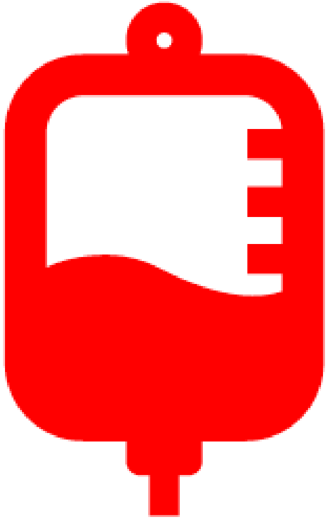
In 2020 there were >40 models for prediction of haemorrhage after injury

Many share input variables e.g. SBP, bloods and radiology

	ABC	TASH	Mina	Shock Index	Code Red
Publication Year	2009	2006	2013	2011	2016
Intended Location	IH	IH	IH	PH	PH
Internal validation (n)	596	6044	13961	n/a	126
External validation (n)*	5147	5147	1245	535	53
Impact study performed	retrospective	No	No	No	No
AUROC in external validation	0.76	0.89	~0.70	0.77	unknown
Major haemorrhage definition	1	2	3	1	4

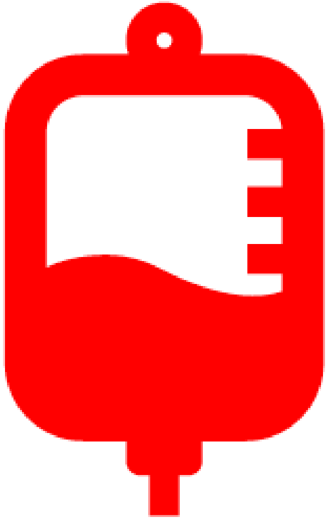
Current knowledge and availability of machine learning across the spectrum of trauma science

Tobias Gauss[a], Zane Perkins[b] and Thorsten Tjardes[c]



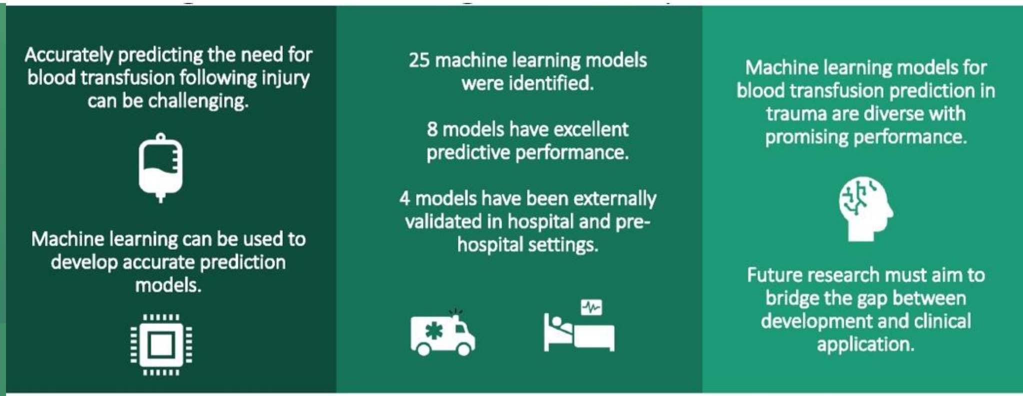
Prediction of massive transfusion is overrepresented.

Received vs required



Predicted interventions correspond to therapeutic actions that clinicians have performed in the derivation cohorts. In consequence, the models predict past physician behaviour

The Journal of Trauma and Acute Care Surgery



SYSTEMATIC REVIEW W/O META-ANALYSIS

Predicting blood transfusion following traumatic injury using machine learning models: A systematic review and narrative synthesis

Oakley, William MSc[1]; Tandle, Sankalp MBChB[2]; Perkins, Zane PhD, FRCS[2]; Marsden, Max PhD, FRCS[1]

The Journal of Trauma and Acute Care Surgery

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SYSTEMATIC REVIEW W/O META-ANALYSIS

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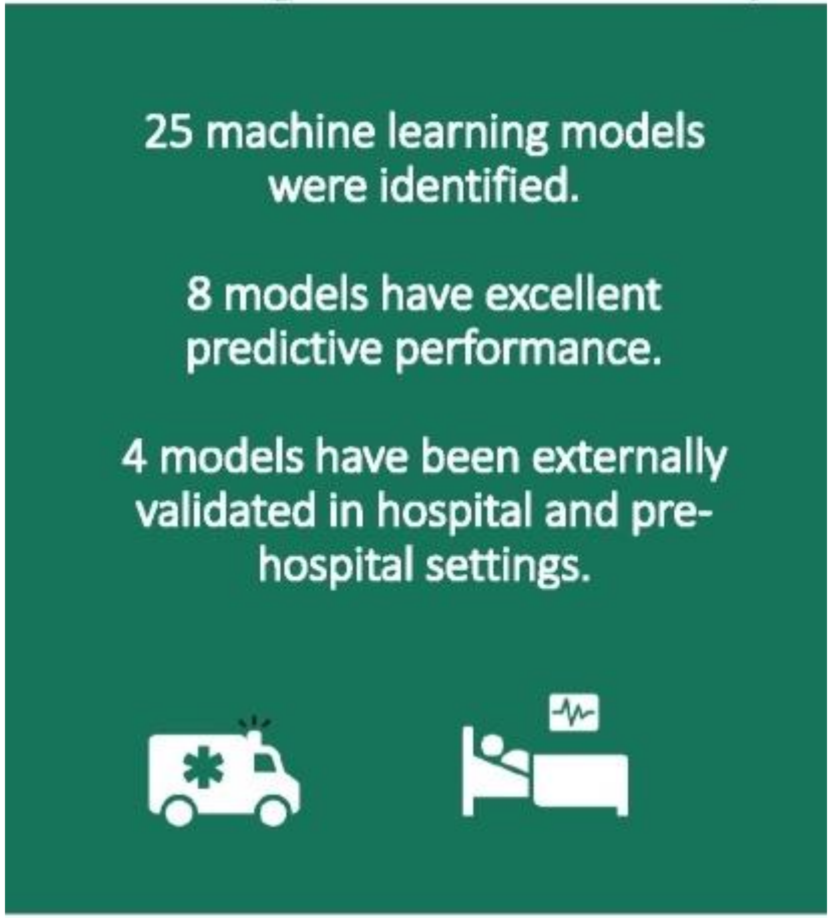


- Models had between 3 and 23 input variables
- Only 2 models reported measures of calibration

Predictors

Vital Signs

24 models

Demographics

12 models

Photoplethysmography Waveforms

5 models

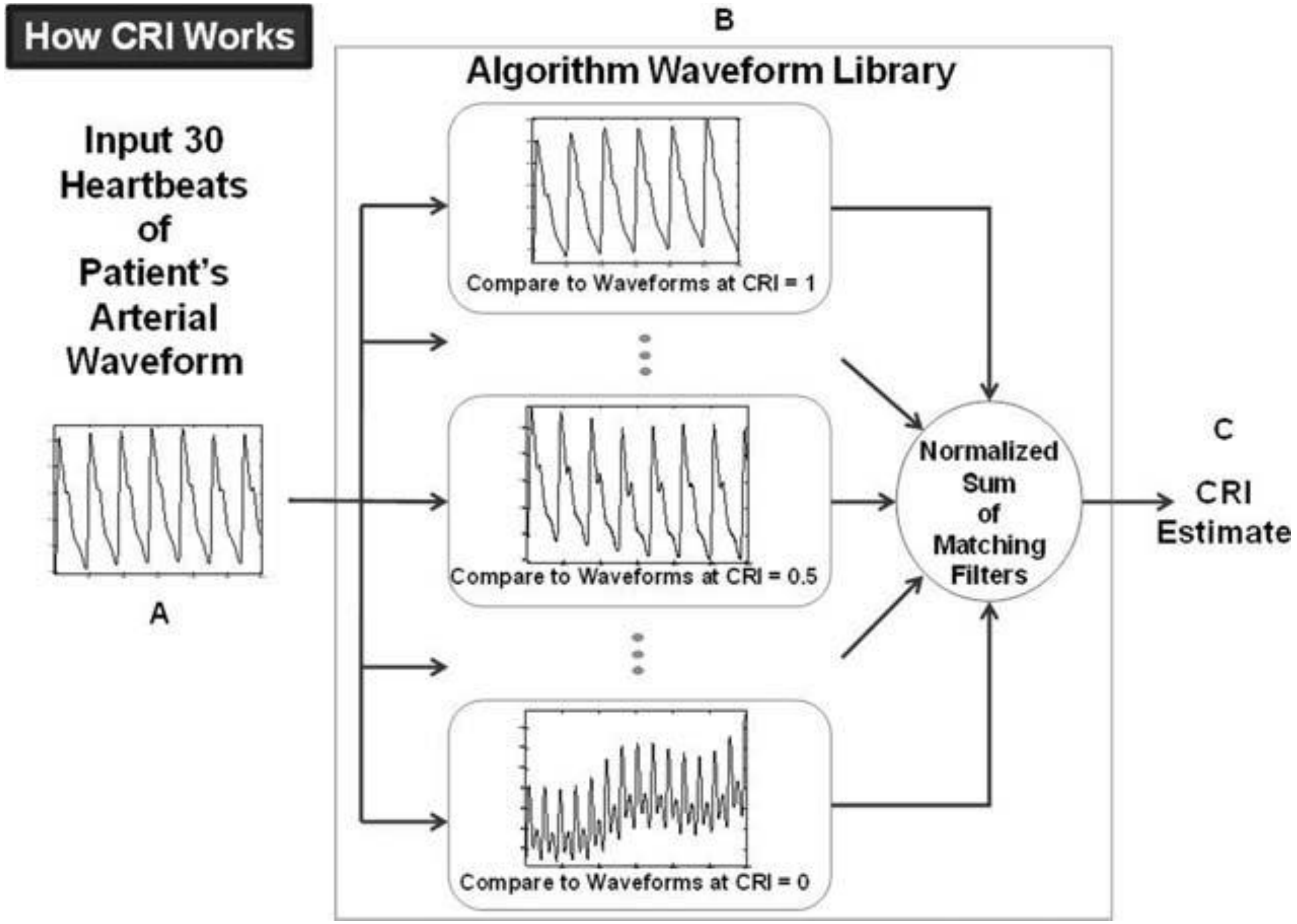
Laboratory Results

12 models

CT Interpretation

1 model

Feature Extraction



24 different outcomes

Blood Transfusion
Transfusion within 2 hours
Transfusion within 3 hours
Transfusion within 4 hours
Transfusion within 6 hours
Transfusion within 12 hours
Transfusion within 24 hours
Transfusion within 48 hours
Transfusion within 72 hours
Transfusion of universal donor Group O un-cross-matched PRBC
Prediction of extensive blood transfusion (>350ml)
Rapid transfusion (>5 units in 4 hours)

Massive Transfusion
10 units PRBC in 24 hours
4 units PRBC in 4 hours
6 units PRBC in 6 hours
Critical Administration Threshold (3 units PRBC in 60 minutes)
Resource Intensity greater than or equal to 4
5 units or greater PRBC within 5 hours of admission
10 units of greater PRBC within first 12 hours
> 10 units PRBC within 4 hours of admission
>4 units in 1 hour within anticipated ongoing clinical need

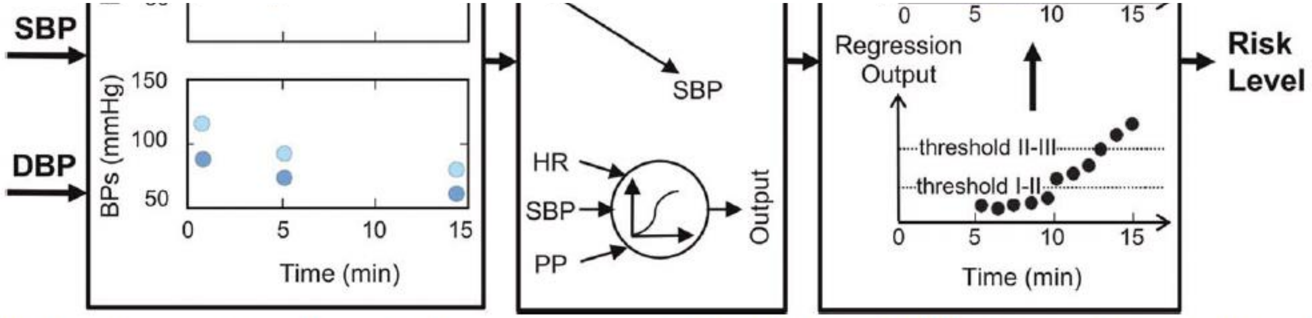
Composite
Lifesaving Intervention
Haemorrhage requiring therapy or haemorrhage control intervention
Prediction of angioembolization, pelvic packing or massive transfusion
Prediction of shock

SHOCK, Vol. 60, No. 2, pp. 199–205, 2023

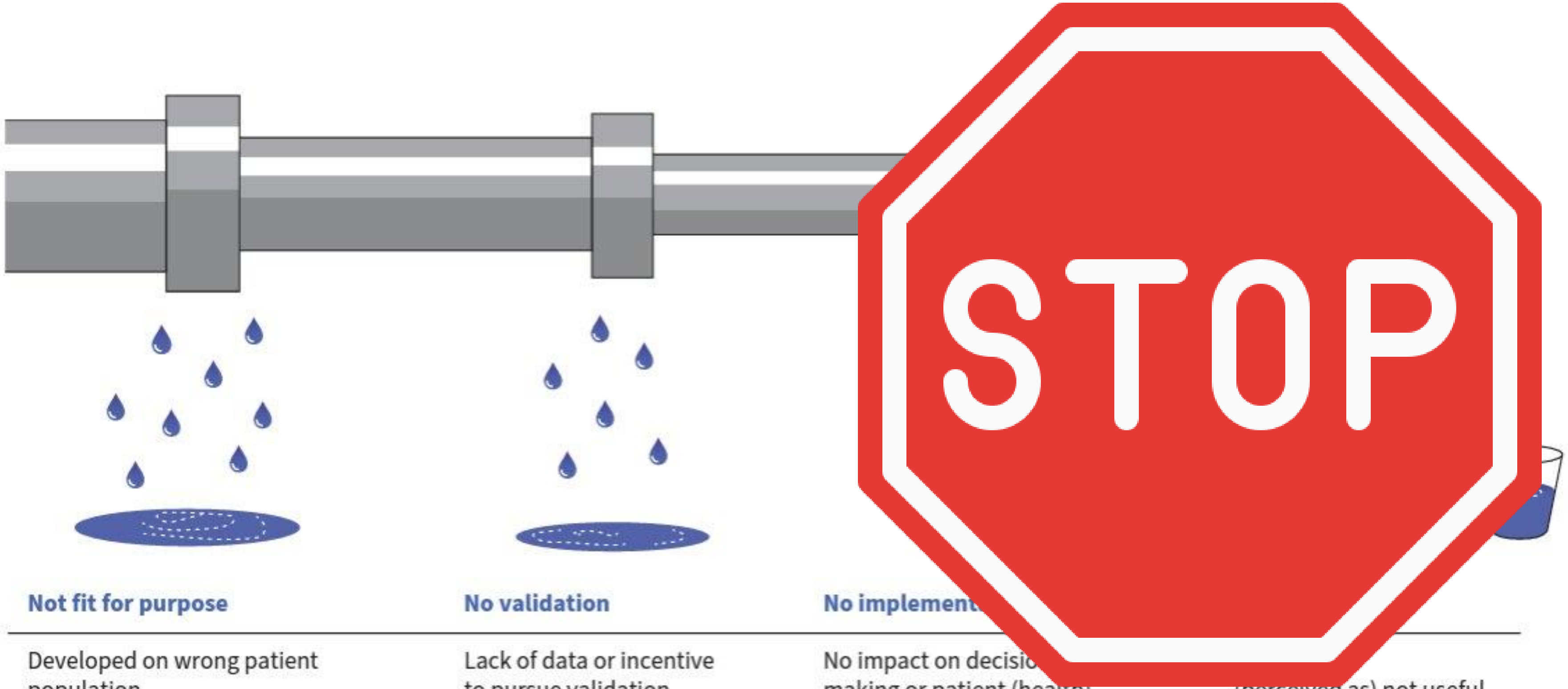
OPEN

APPRAISE-HRI: AN ARTIFICIAL INTELLIGENCE ALGORITHM FOR TRIAGE OF HEMORRHAGE CASUALTIES

FDA Clears First AI Software for Hemorrhage Triage of Combat Casualties



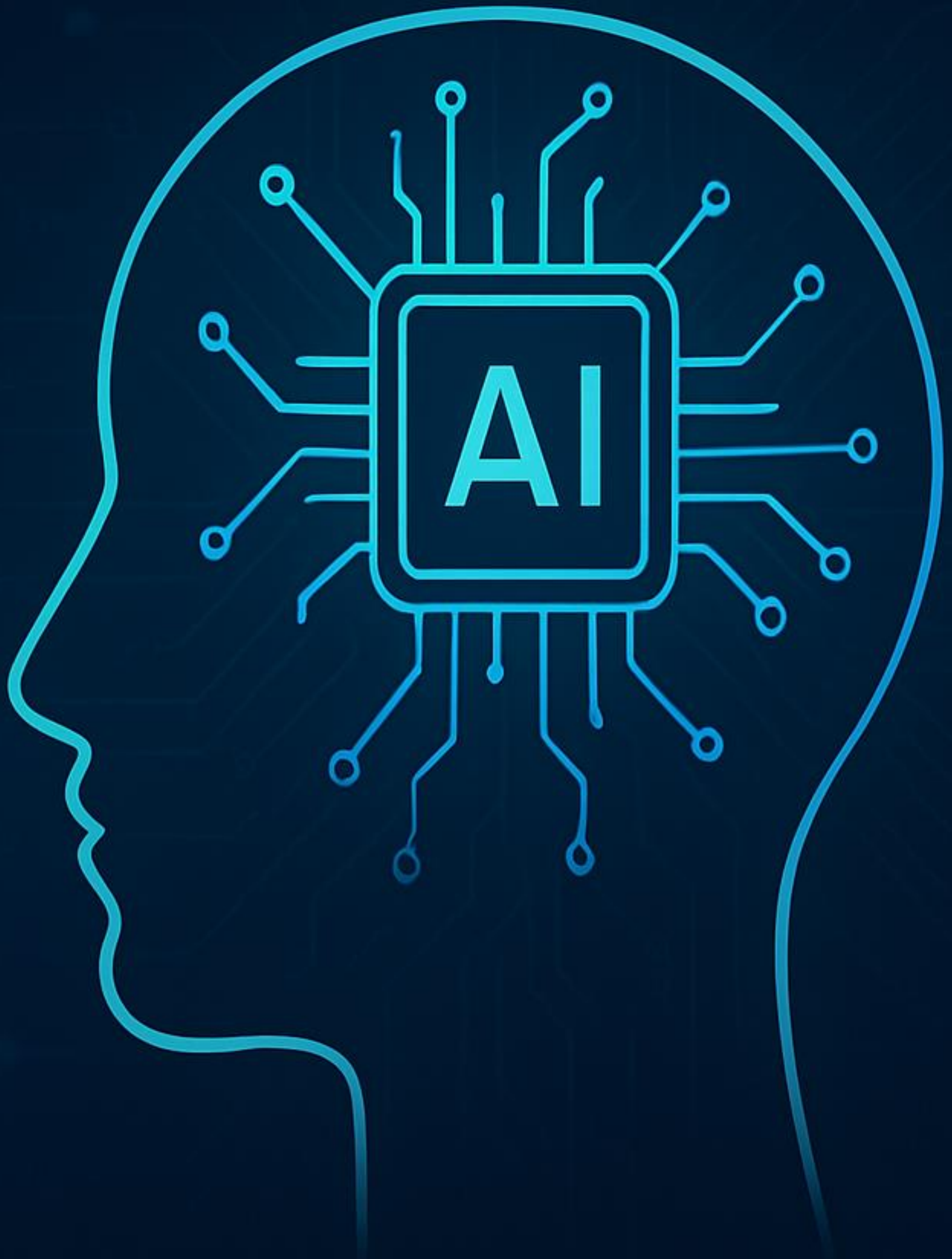
AISE-HRI algorithm receives three vital signs as inputs (HR, SBP, and DBP) and provides a risk level as its ou

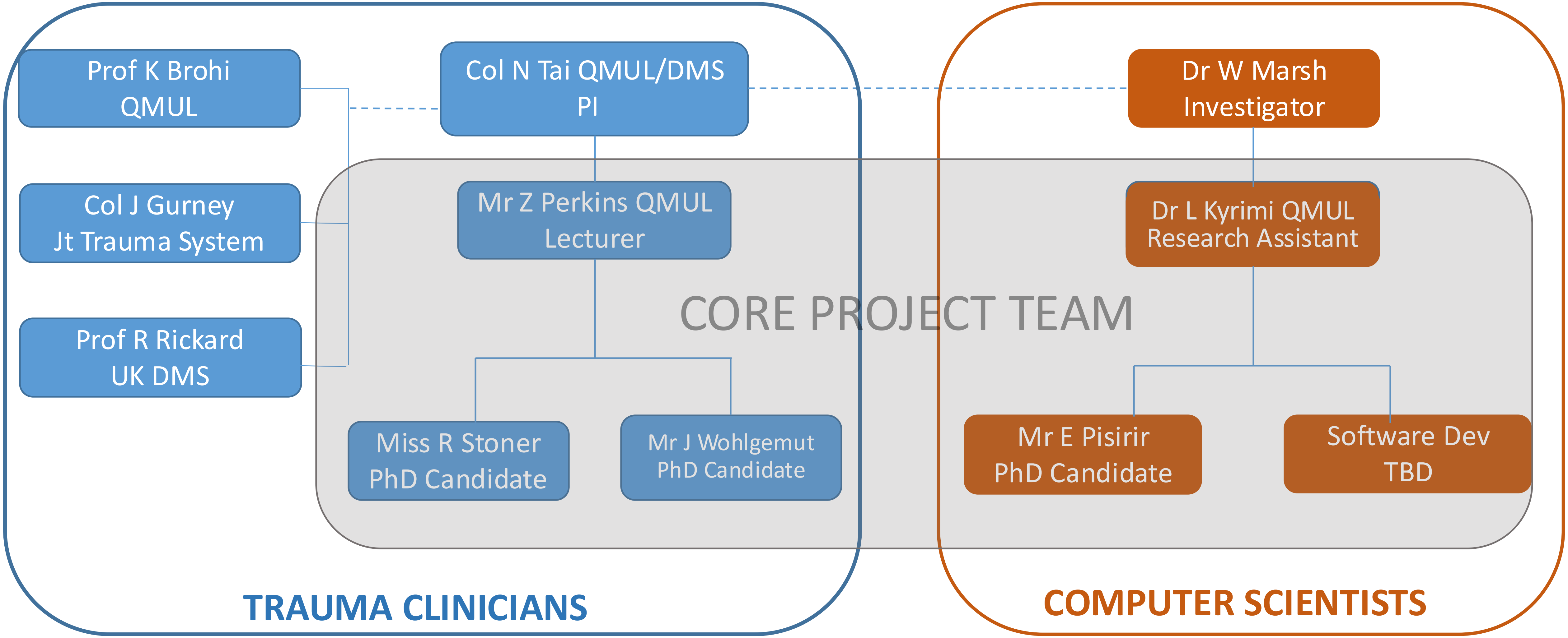


Not fit for purpose	No validation	No implement	
Developed on wrong patient population	Lack of data or incentive to pursue validation studies	No impact on decisio making or patient (health) outcomes	(perceived as) not useful
Expensive or non-available predictors	Incompletely reported prediction model	No software developed to implement and use the model	Predictions not trusted
Time intensive to use model	Poorly developed or overfitted model	Requirements for adherence to (medical device) regulations	Model not transparent enough, or no tools available to enhance its use in practice
Outcome measured unreliably	Proprietary model code	Cost(-effectiveness) of using proprietary model	Model (perceived as) outdated

FIGURE 1 Leaky prognostic model adoption pipeline. Examples of reasons for failed prediction model adoption in clinical practice.

Bayesian Networks

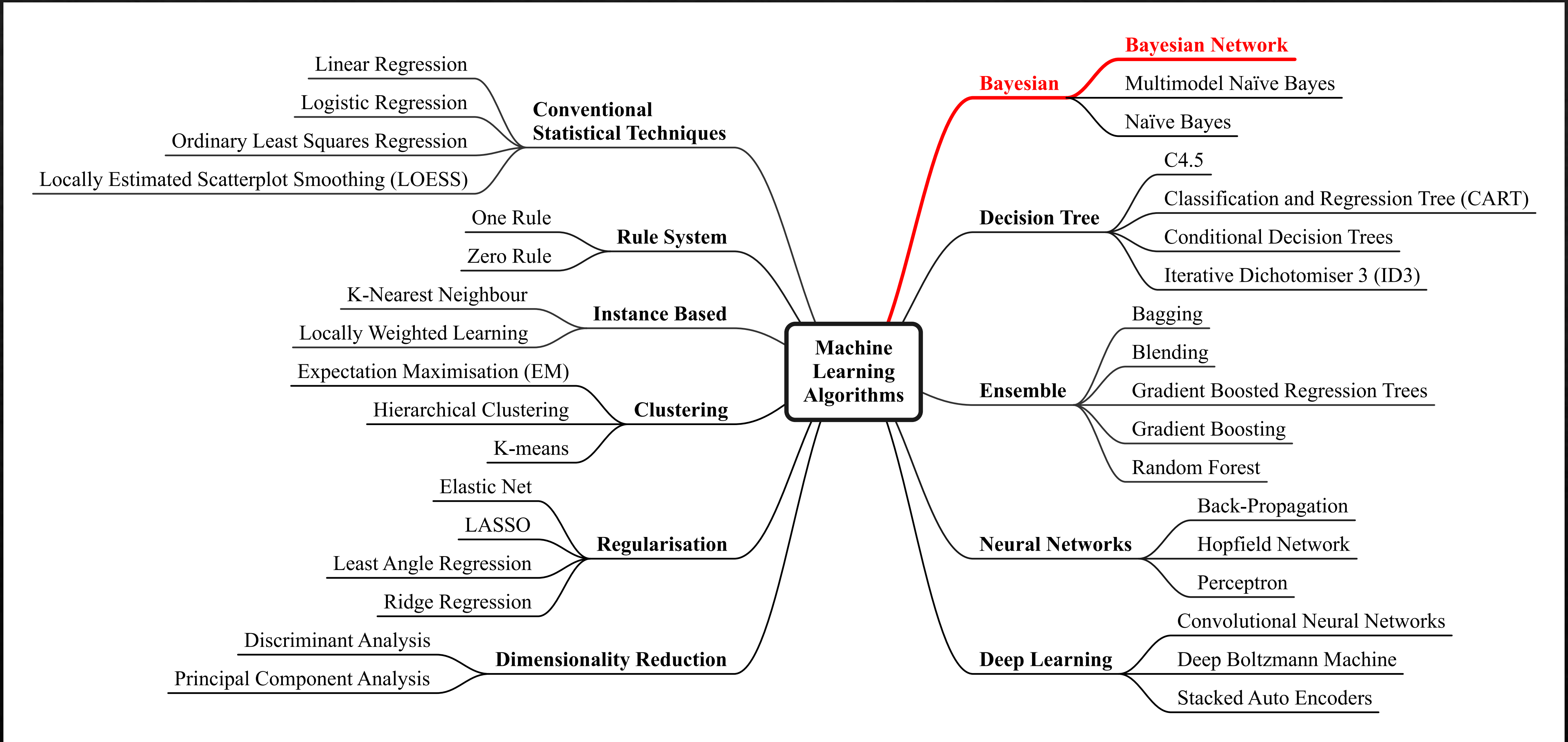




COMBAT-AID DEVELOPMENT TEAM

COMPUTER BATTLEFIELD ASSISTANCE IN TRAUMA CARE & INJURY DECISION SUPPORT

SUPPORTED BY US DOD W81XWH-19-2-0047 - Exploitation of Bayesian Networks for Clinical Decision Support on the Battlefield


Machine Learning Algorithms
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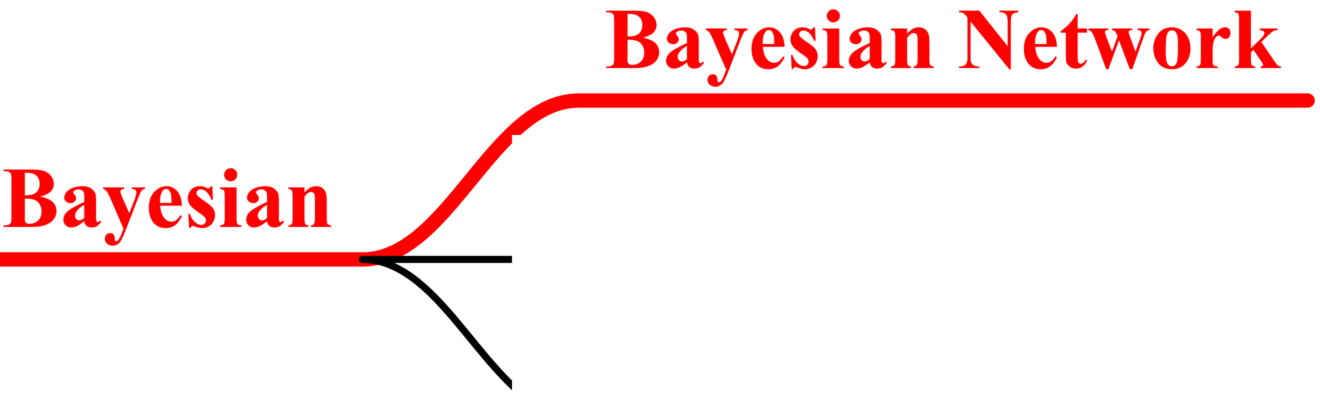
Neural Networks
Back-Propagation
Hopfield Network
Perceptron
Deep Learning
Convolutional Neural Networks
Deep Boltzmann Machine
Stacked Auto Encoders


Bayesian Network
Bayesian

Advantages of Bayesian Networks

Explicit modeling of uncertainty
Combine data with domain knowledge
Flexibility to update beliefs and incorporate new evidence
Ability to handle complex dependencies
Support inference in the presence of missing data
Support for probabilistic inference and reasoning under uncertainty
Support interventional and counterfactual reasoning
Explainable

Advantages of Bayesian Networks

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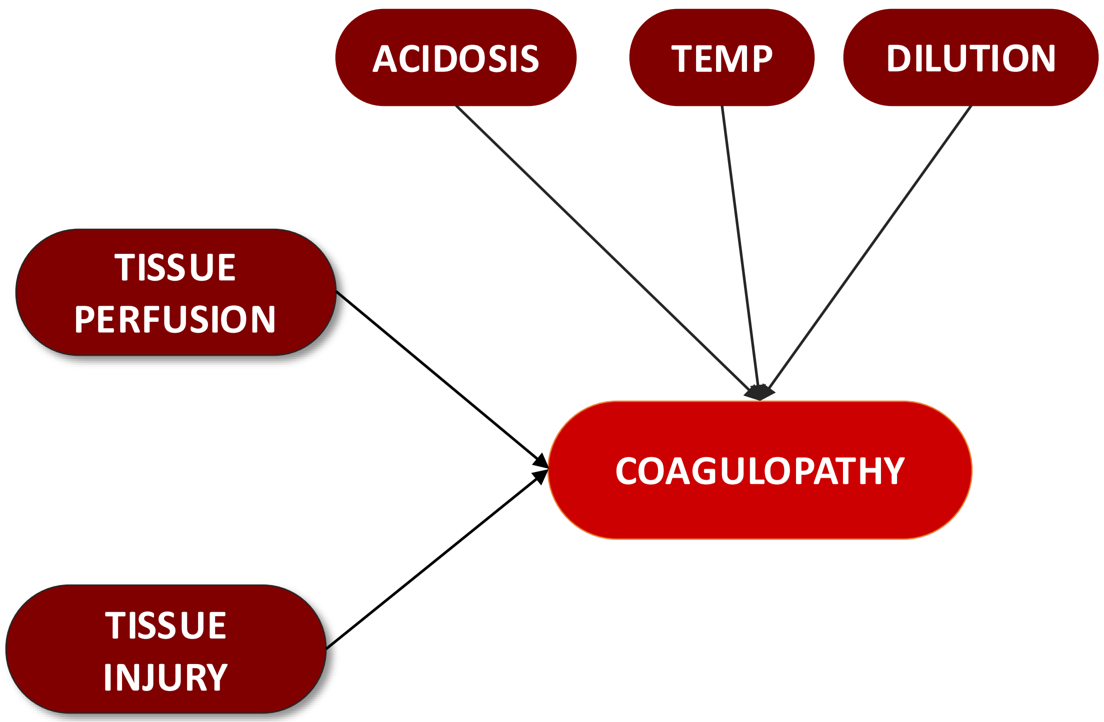
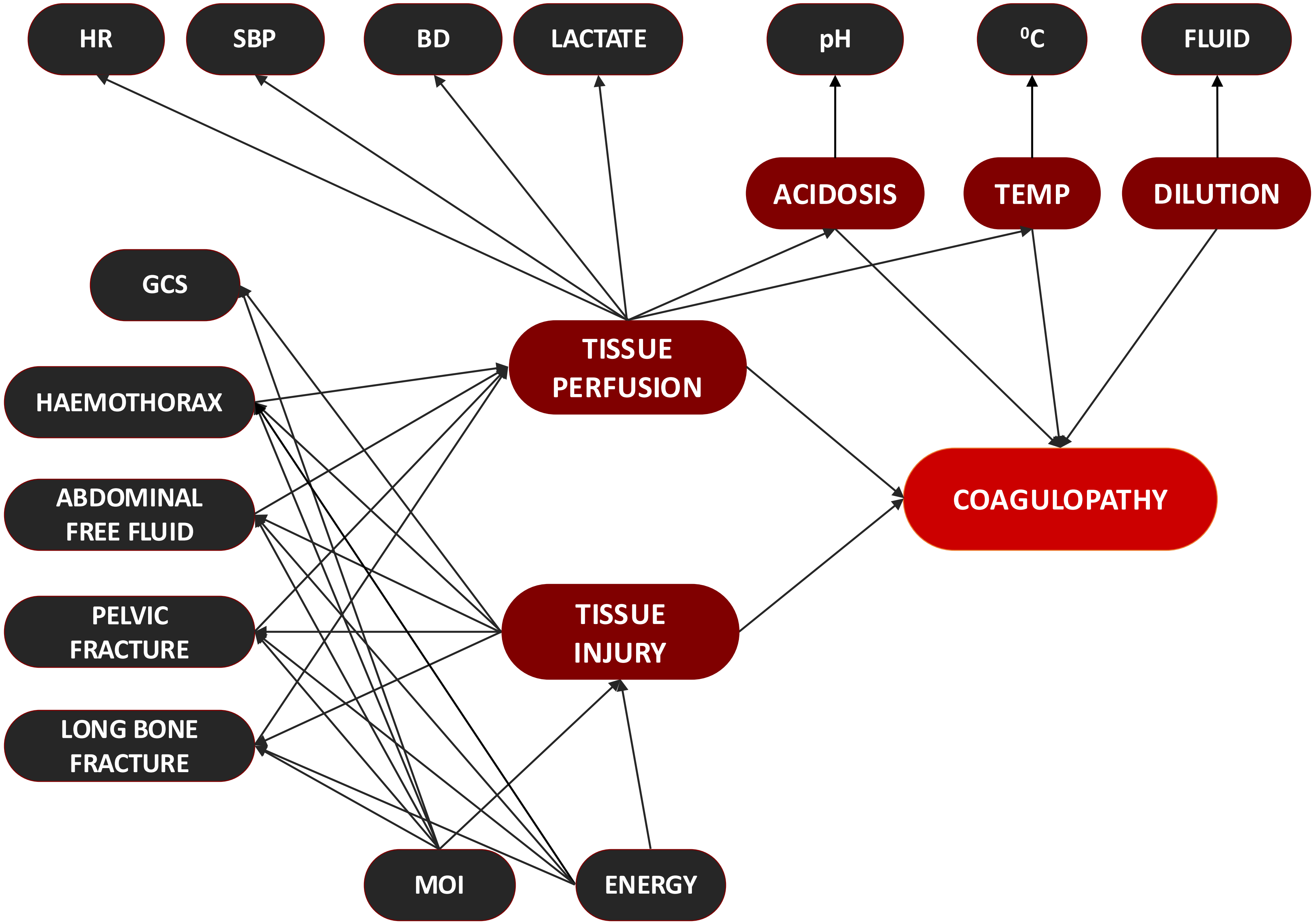
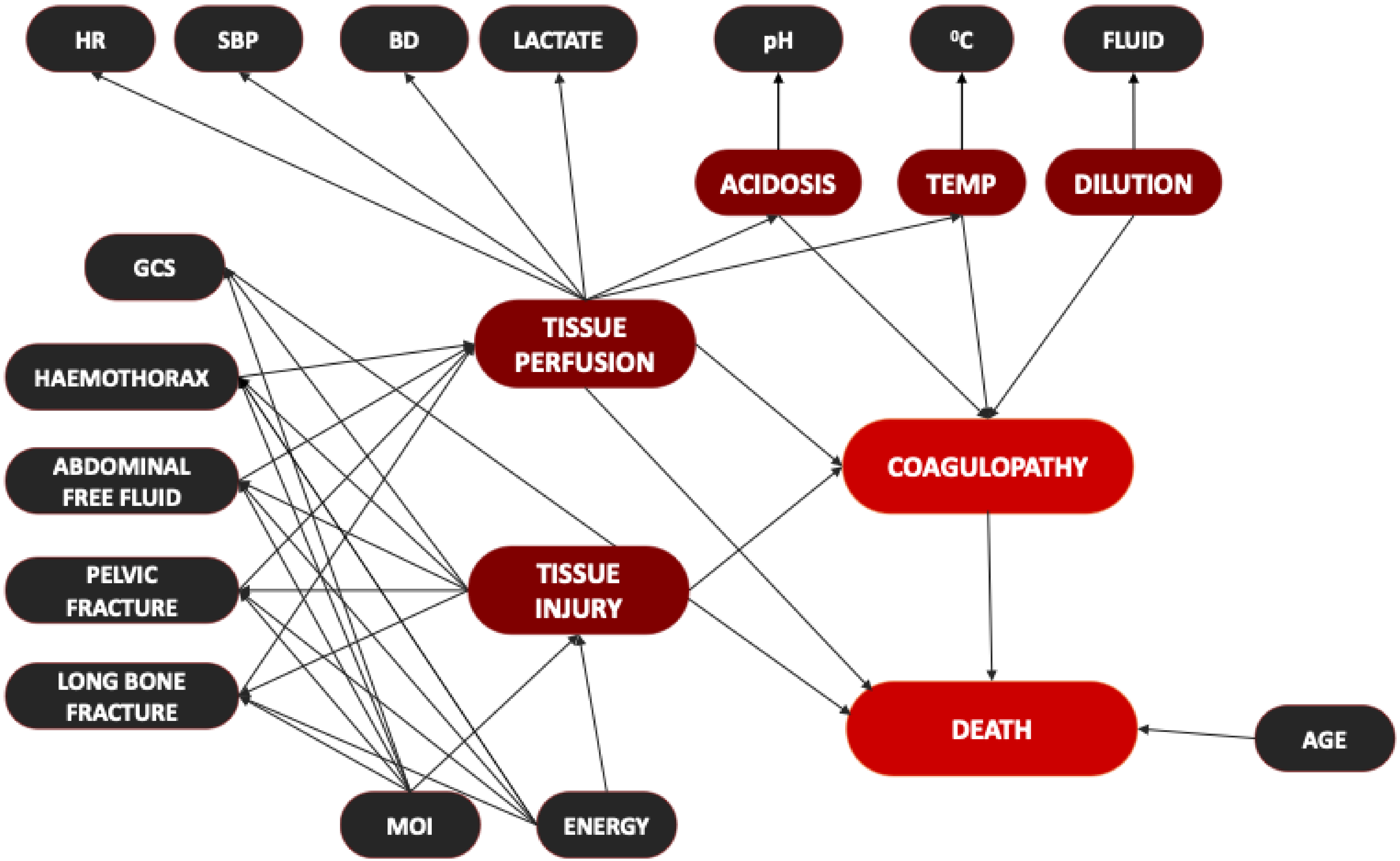
Explainable

COAGULOPATHY


ACIDOSIS
TEMP
DILUTION
TISSUE PERFUSION
COAGULOPATHY
TISSUE INJURY


HR
SBP
BD
LACTATE
pH
⁰C
FLUID
ACIDOSIS
TEMP
DILUTION
GCS
HAEMOTHORAX
ABDOMINAL FREE FLUID
PELVIC FRACTURE
LONG BONE FRACTURE
TISSUE PERFUSION
TISSUE INJURY
COAGULOPATHY
MOI
ENERGY


HR
SBP
BD
LACTATE
pH
^{0}C
FLUID
ACIDOSIS
TEMP
DILUTION
GCS
HAEMOTHORAX
ABDOMINAL FREE FLUID
PELVIC FRACTURE
LONG BONE FRACTURE
TISSUE PERFUSION
TISSUE INJURY
COAGULOPATHY
DEATH
AGE
MOI
ENERGY

Journal of Biomedical Informatics 48 (2014) 28–37

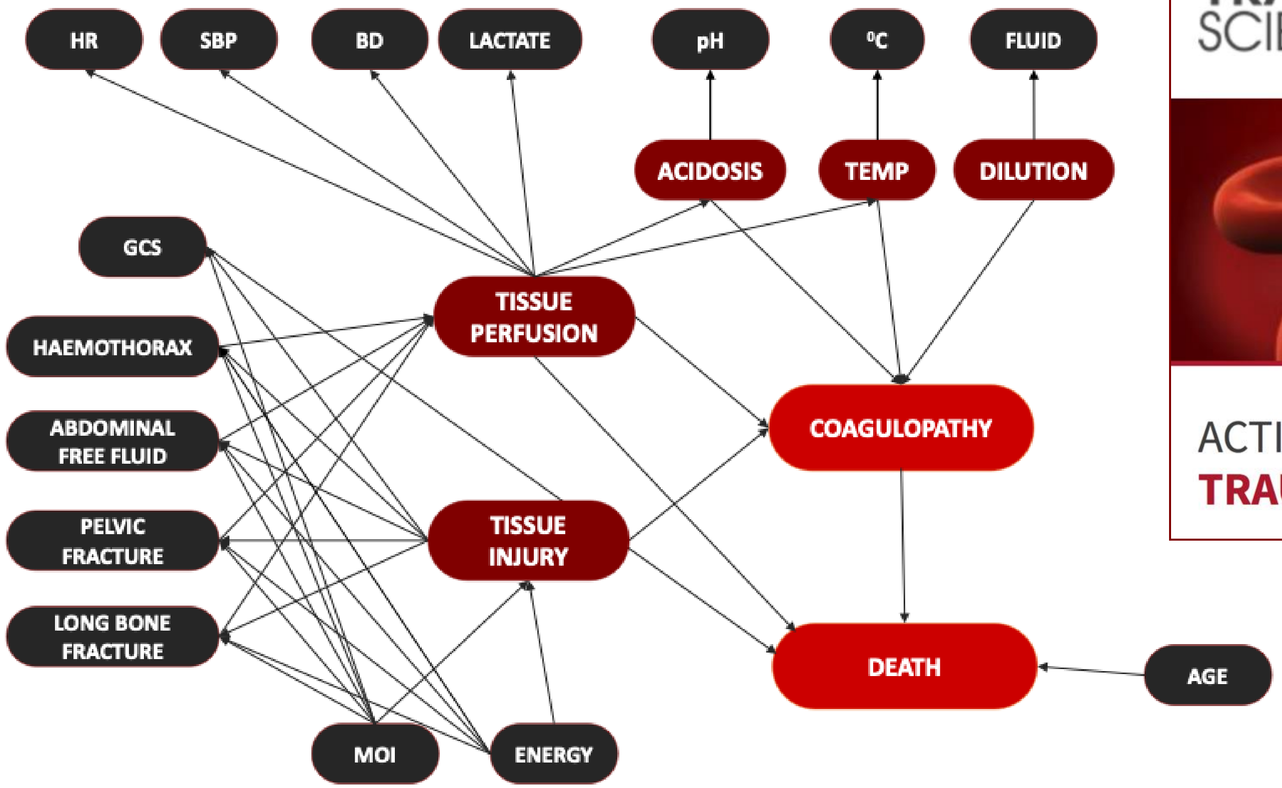
Not just data: A method for improving prediction with knowledge

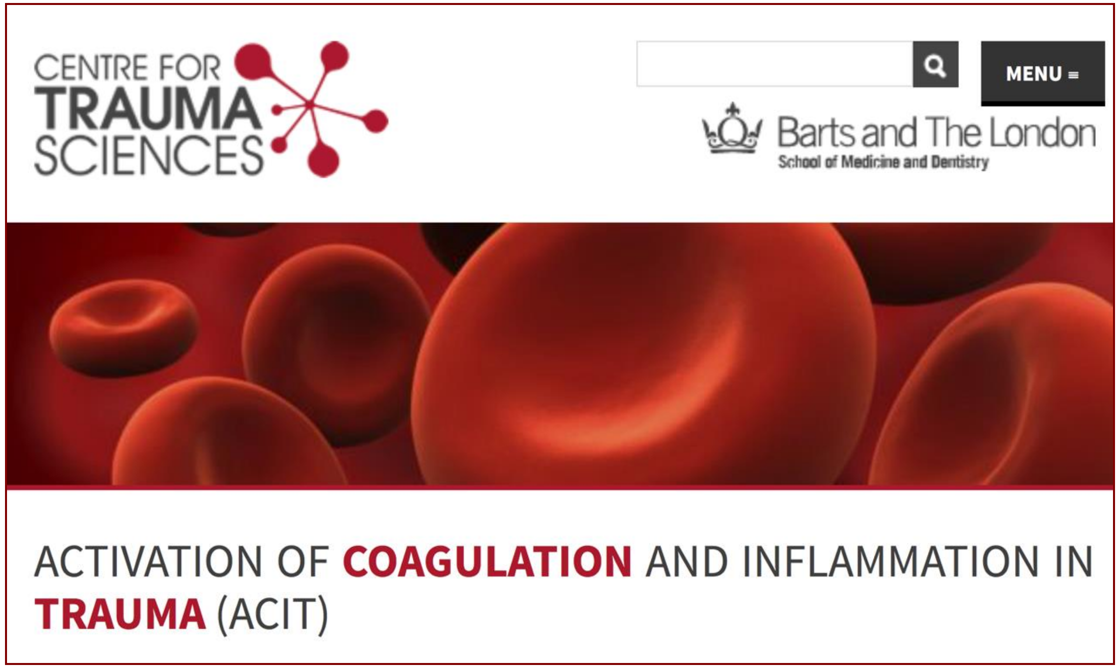
Barbaros Yet[a,*], Zane Perkins[b], Norman Fenton[a], Nigel Tai[c], William Marsh[a]

Journal of Biomedical Informatics 52 (2014) 373–385

Combining data and meta-analysis to build Bayesian networks for clinical decision support

Barbaros Yet[a,*], Zane B. Perkins[b], Todd E. Rasmussen[c], Nigel R.M. Tai[d], D. William R. Marsh[a]





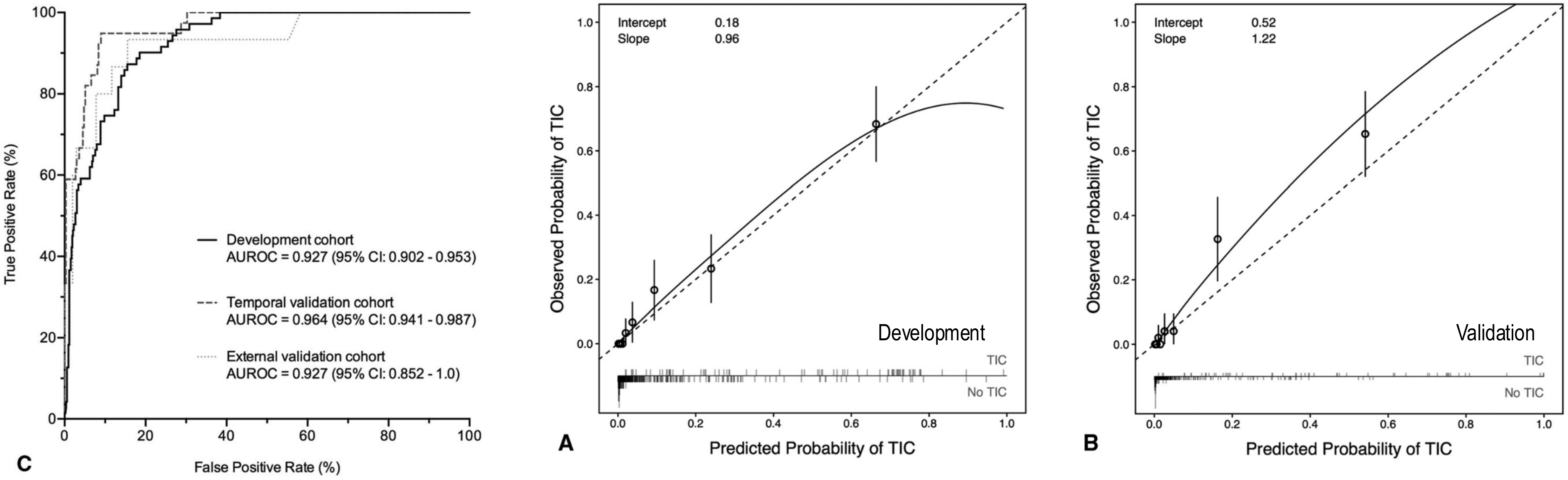
> Ann Surg. 2021 Dec 1;274(6):e1119-e1128. doi: 10.1097/SLA.0000000000003771.

ORIGINAL ARTICLE

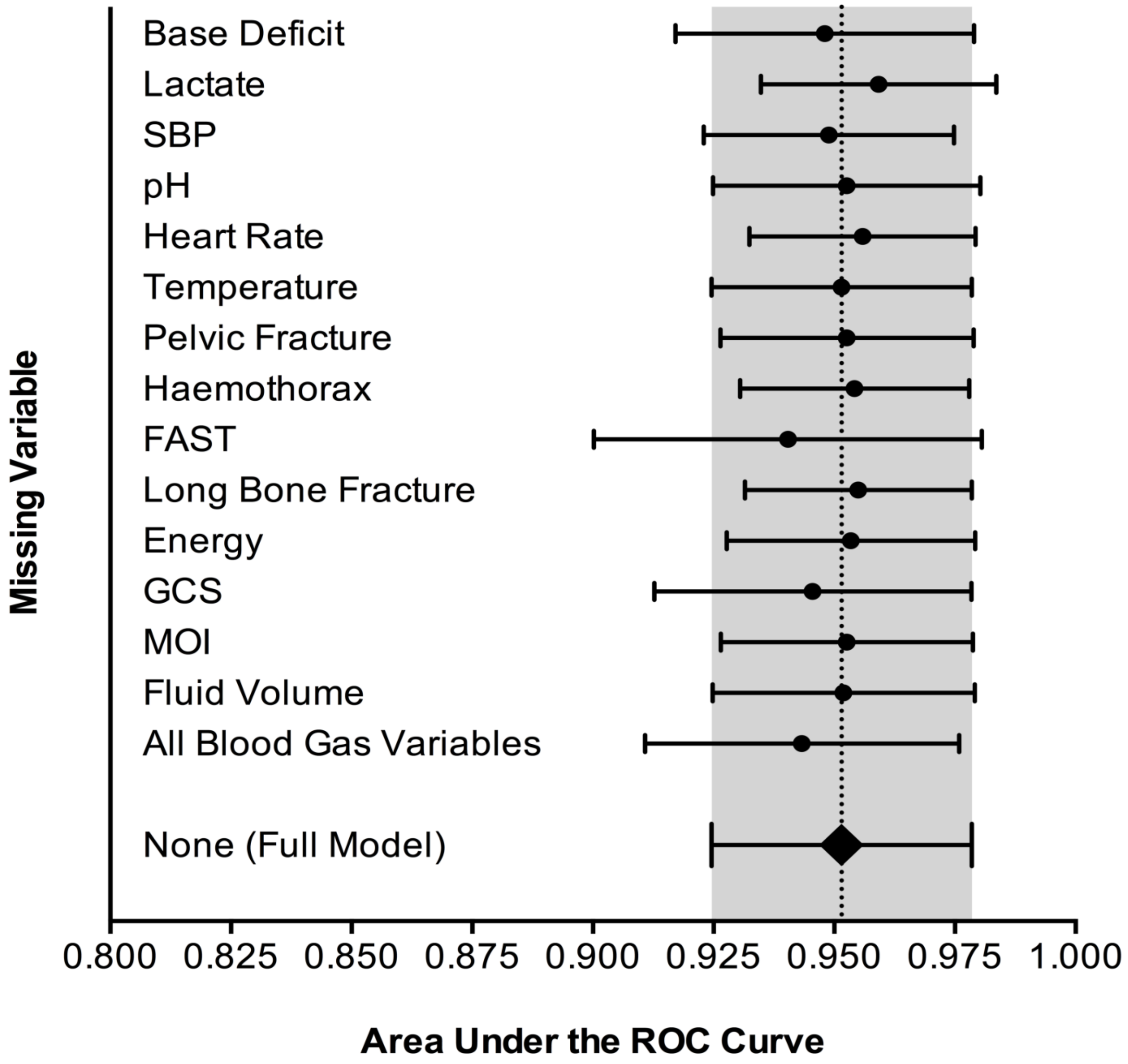
Early Identification of Trauma-induced Coagulopathy

Development and Validation of a Multivariable Risk Prediction Model

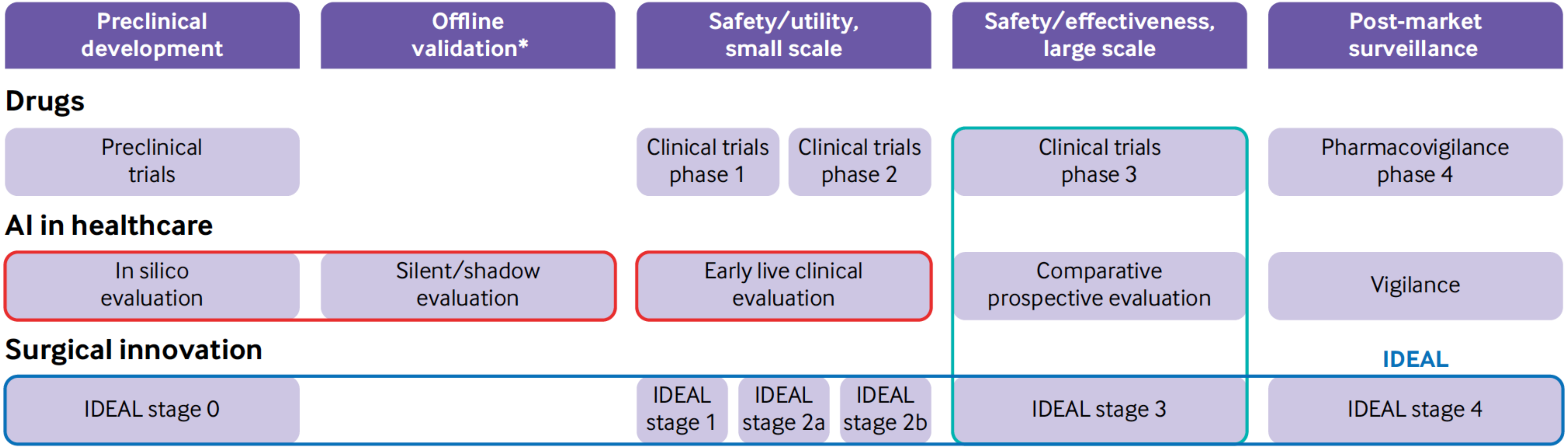
*Zane B. Perkins, PhD,**✉ *Barbaros Yet, PhD,*† *Max Marsden, BSc,** *Simon Glasgow, PhD,**
William Marsh, PhD,† *Ross Davenport, PhD,** *Karim Brohi, MD,** *and Nigel R. M. Tai, MD**‡



MISSING INFORMATION

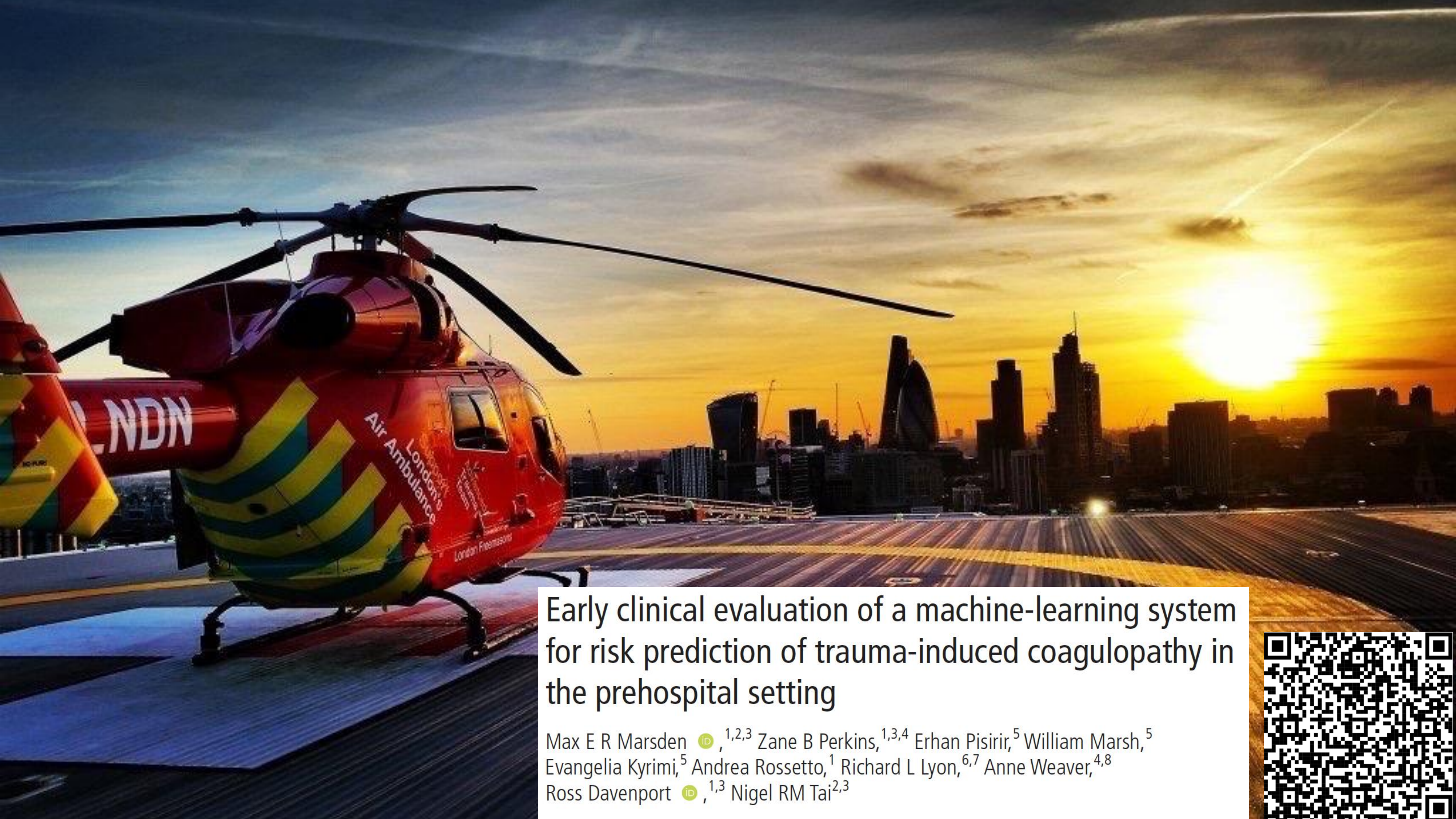


So what about impact?



Preclinical development
Offline validation*
Safety/utility, small scale
Safety/effectiveness, large scale
Post-market surveillance
Drugs
Preclinical trials
Clinical trials phase 1
Clinical trials phase 2
Clinical trials phase 3
Pharmacovigilance phase 4
AI in healthcare
In silico evaluation
Silent/shadow evaluation
Early live clinical evaluation
Comparative prospective evaluation
Vigilance
Surgical innovation
IDEAL
IDEAL stage 0
IDEAL stage 1
IDEAL stage 2a
IDEAL stage 2b
IDEAL stage 3
IDEAL stage 4

(Vasey 2022)



Early clinical evaluation of a machine-learning system for risk prediction of trauma-induced coagulopathy in the prehospital setting

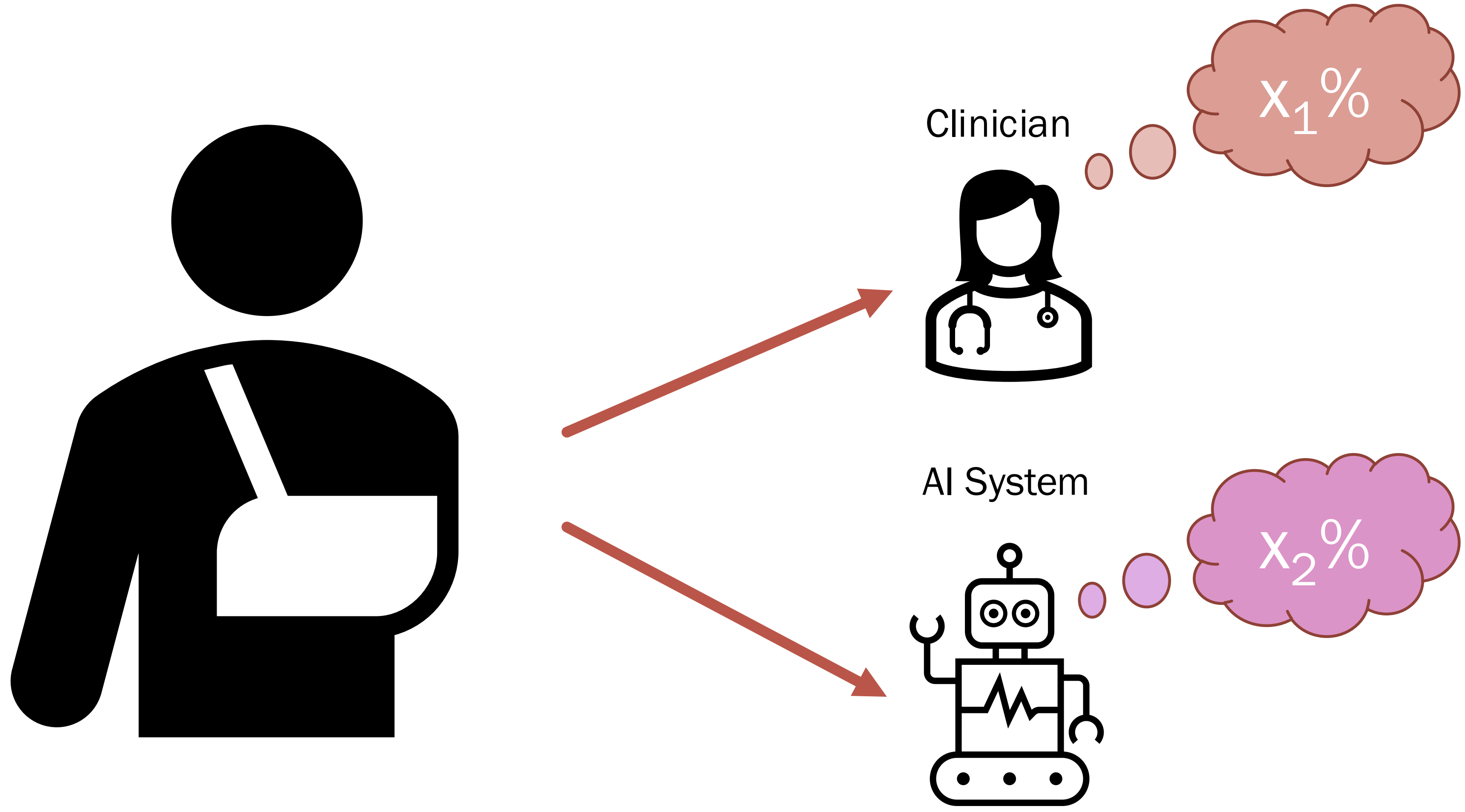
Max E R Marsden ,[1,2,3] Zane B Perkins,[1,3,4] Erhan Pisirir,[5] William Marsh,[5] Evangelia Kyrimi,[5] Andrea Rossetto,[1] Richard L Lyon,[6,7] Anne Weaver,[4,8] Ross Davenport ,[1,3] Nigel RM Tai[2,3]

Method

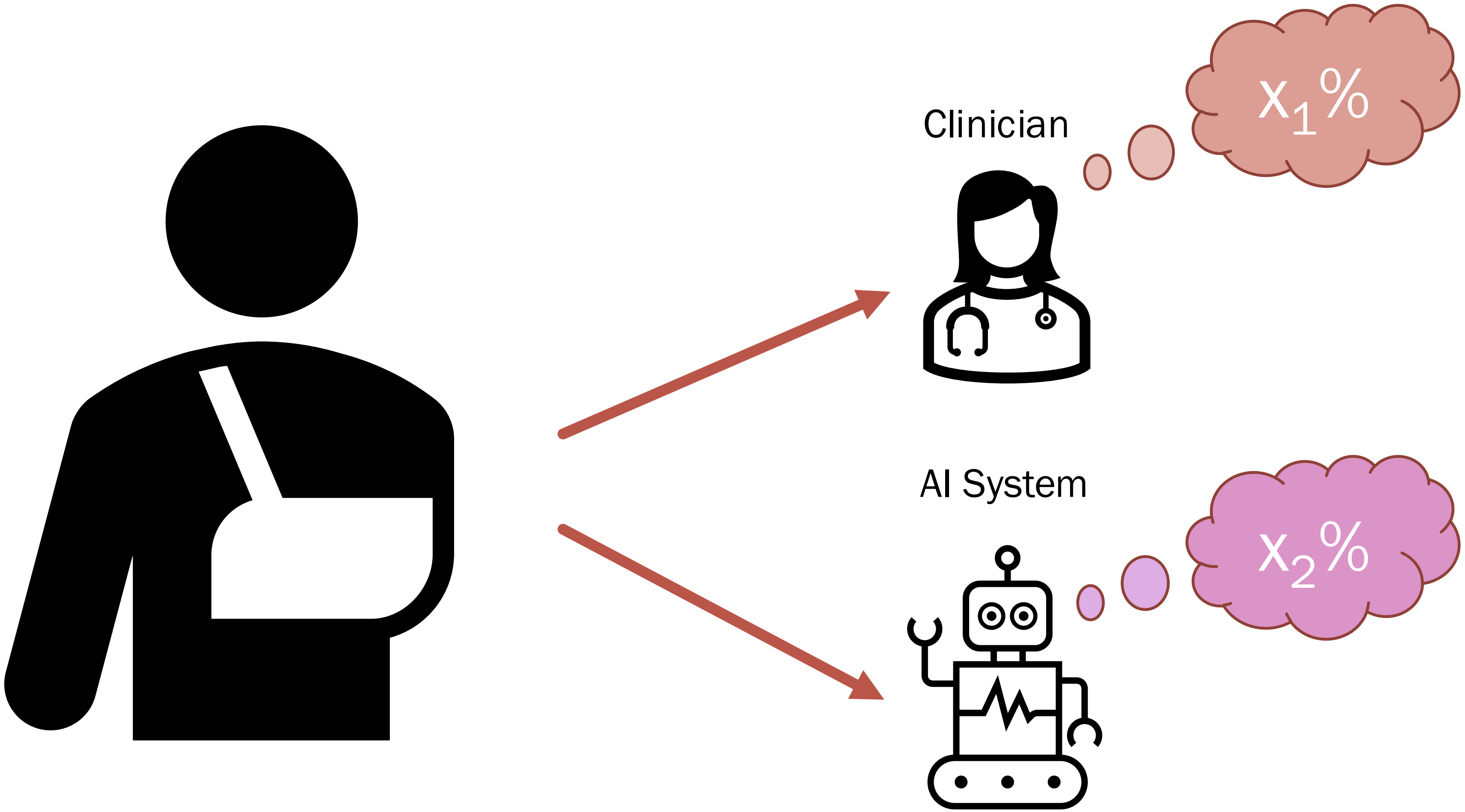
Prospective multicentre impact study at 2 x Air Ambulances

6 months 2018

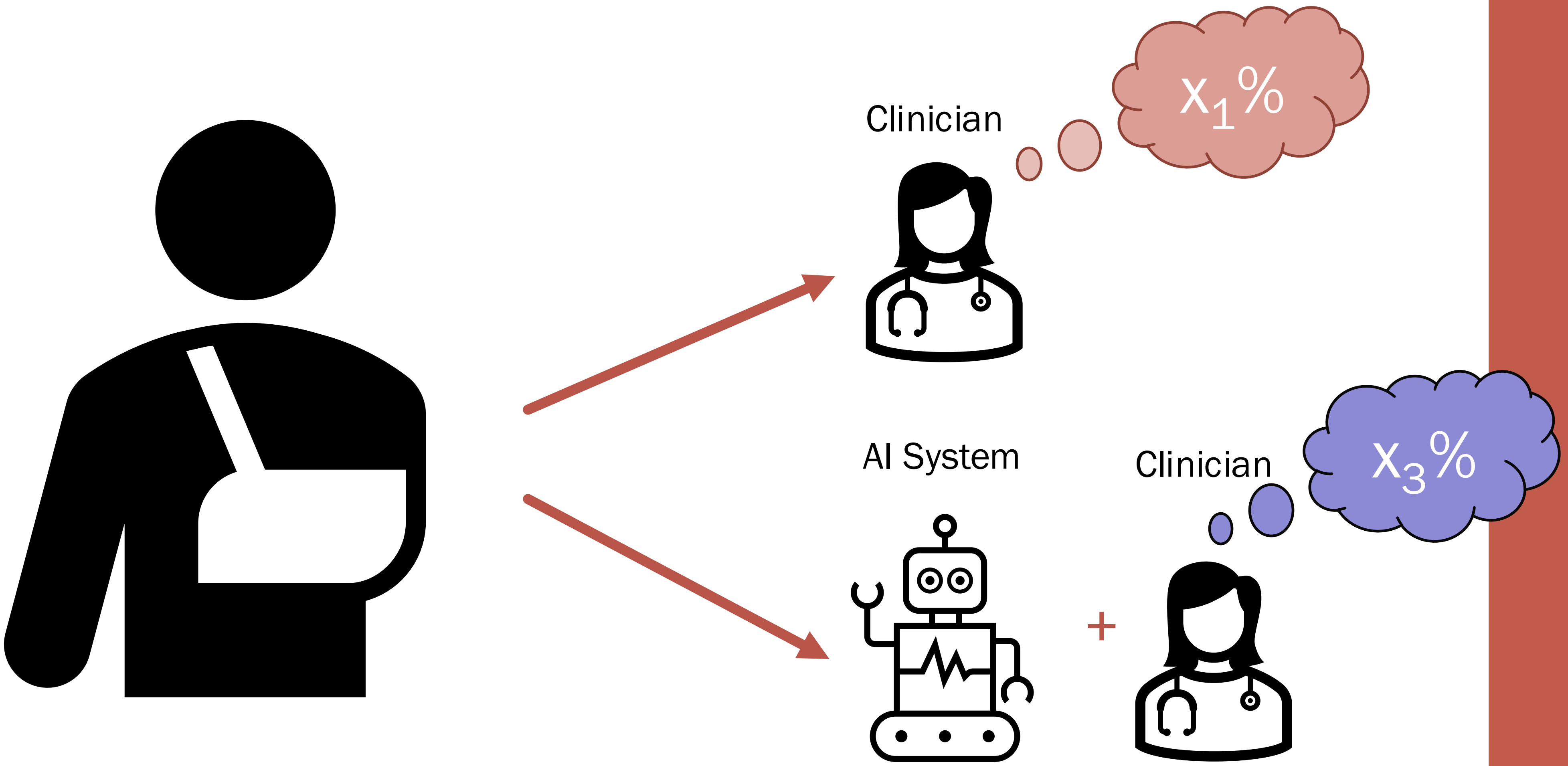
Compared expert pre-hospital clinicians to an AI system



Clinician
$x_1\%$
AI System
$x_2\%$

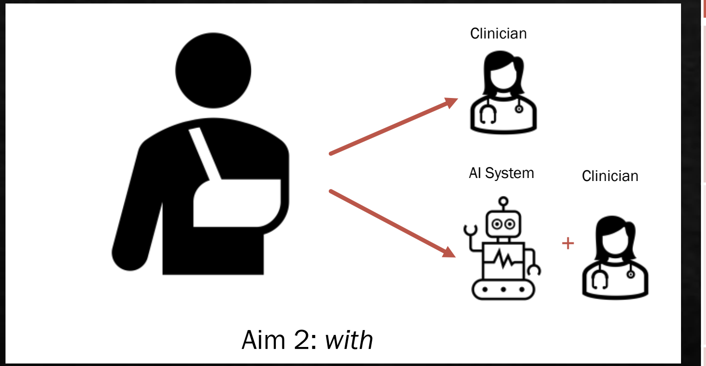


Aim 1: *against*

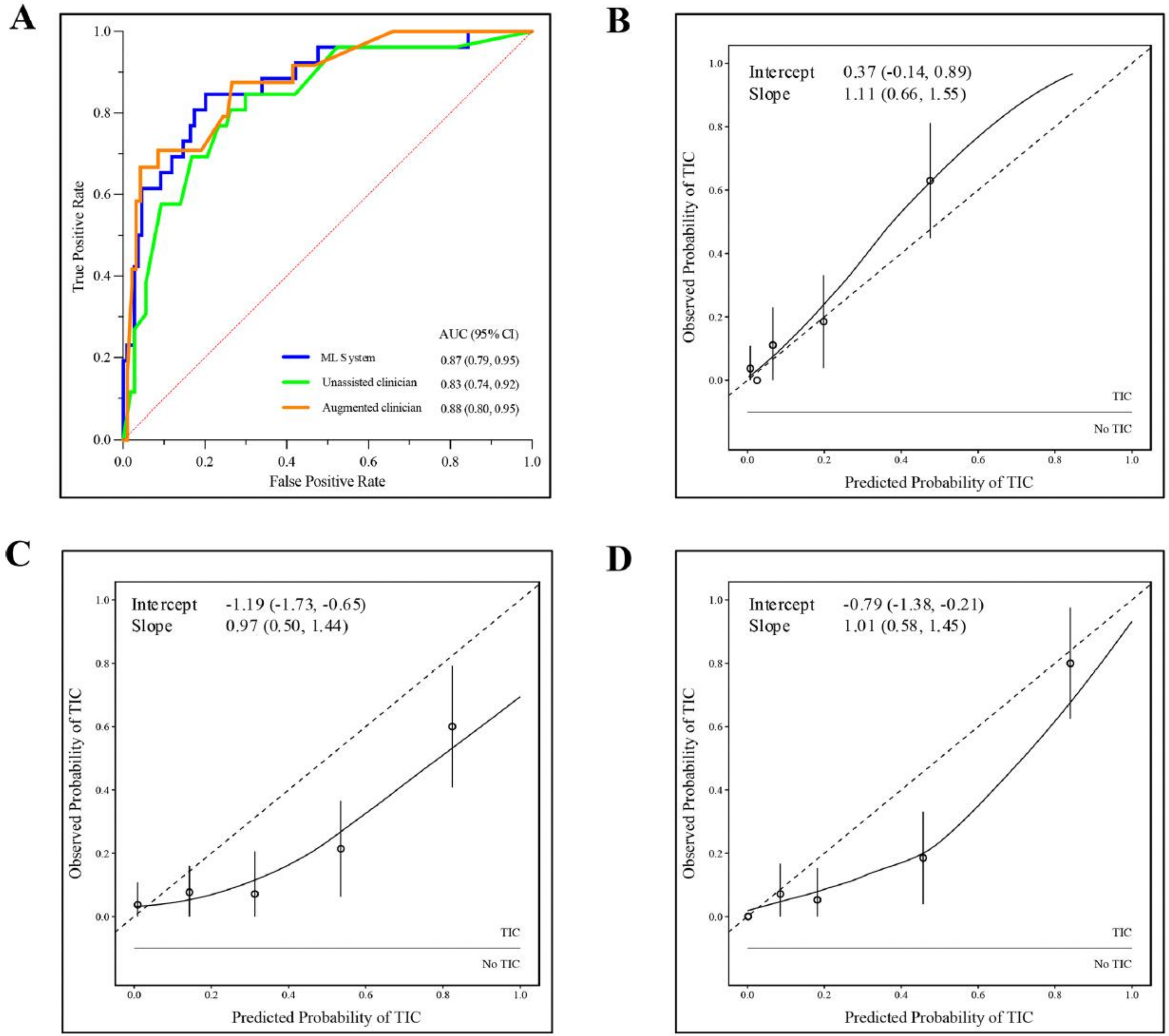


Aim 2: *with*

Risk prediction was better when clinicians were assisted *with* the AI system



	Clinician	AI System & Clinician
Discrimination - AUROC	0.83 (0.74, 0.92)	0.88 (0.80, 0.95)
Calibration	-1.19 (-1.73, -0.65)	-0.79 (-1.38, -0.21)
Accuracy (Brier Skill)	0.00 (-0.41, 0.30)	0.27 (-0.05, 0.51)



A: ML as good as Doctors (AUROC)

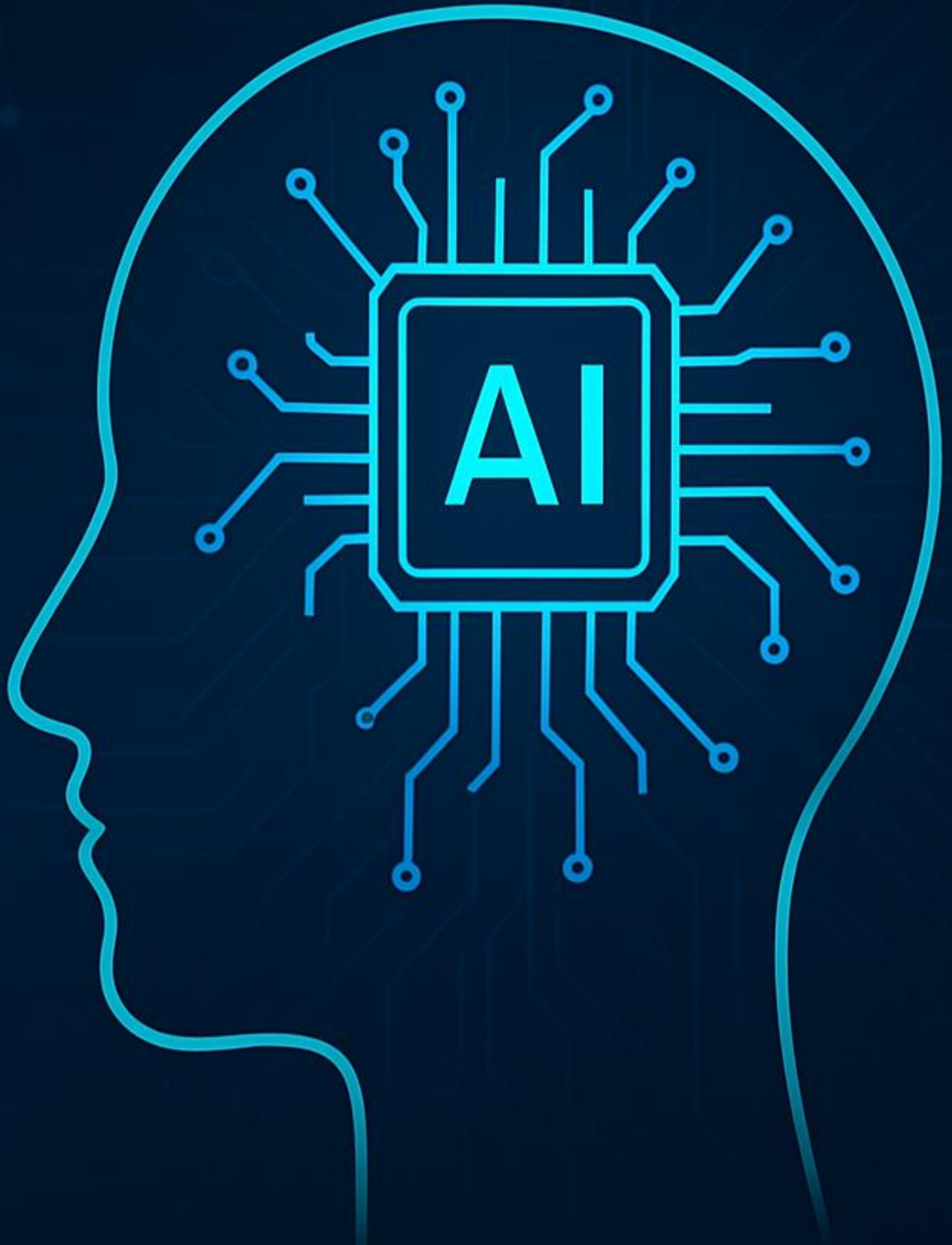
B: ML (Calibration) – tends to small under-triage

C: Docs (Calibration) – tend to moderate over-triage for ”grey and sick”

D: ML+Docs (Calibration) = moderate over-triage for “grey” areas”

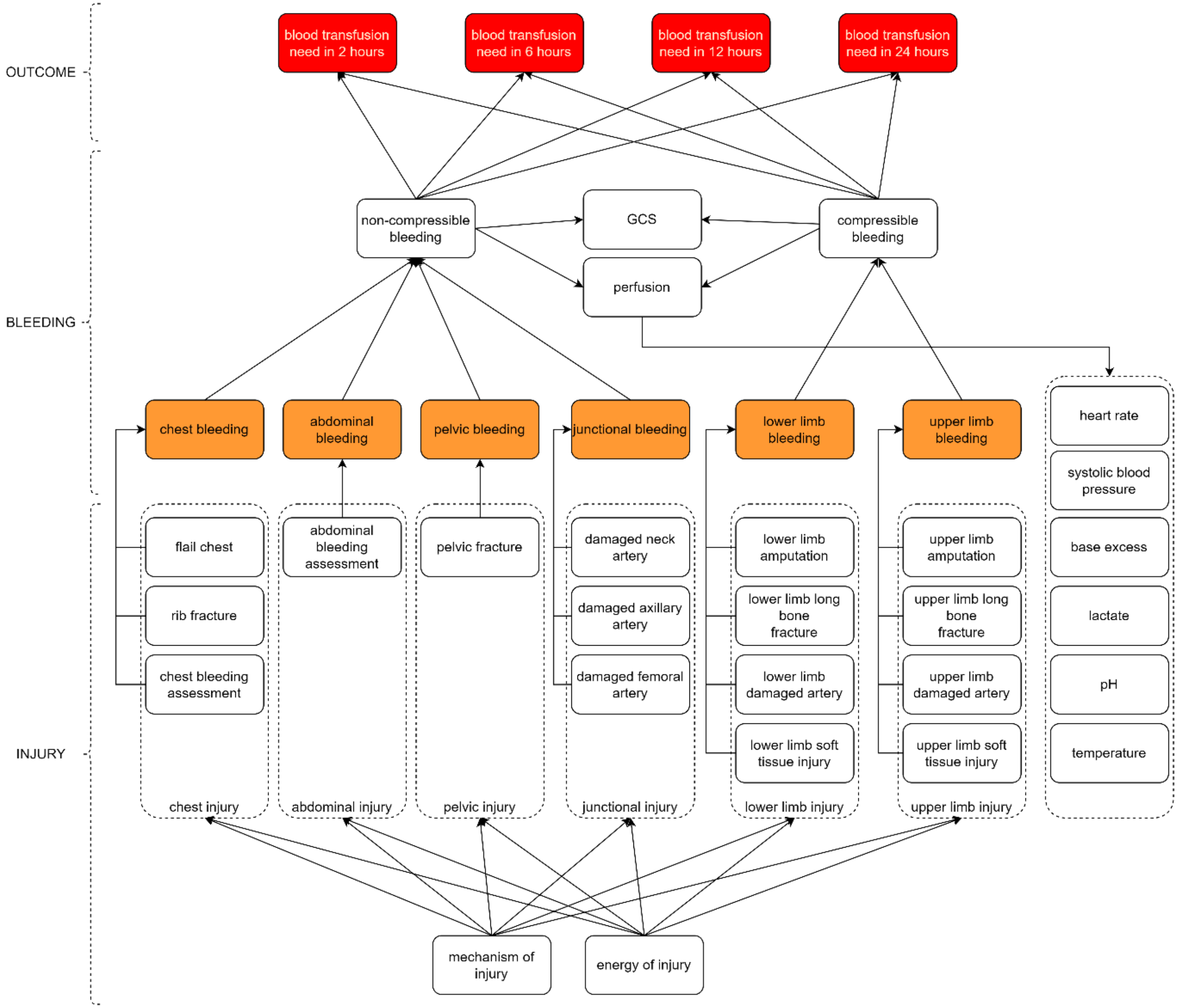
Human with AI produced the best predictions

Bleeding and Bayes



Predict the transfusion requirement at 2, 6, 12 and 24 hours

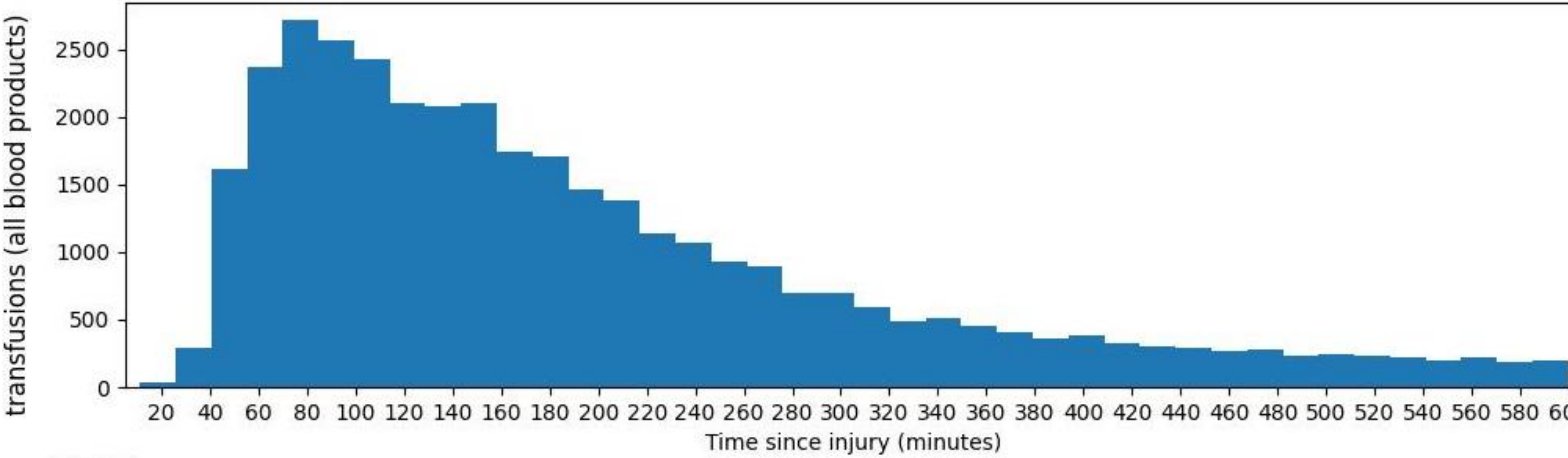
Using pre-hospital information



Training Dataset First 10 hours after injury

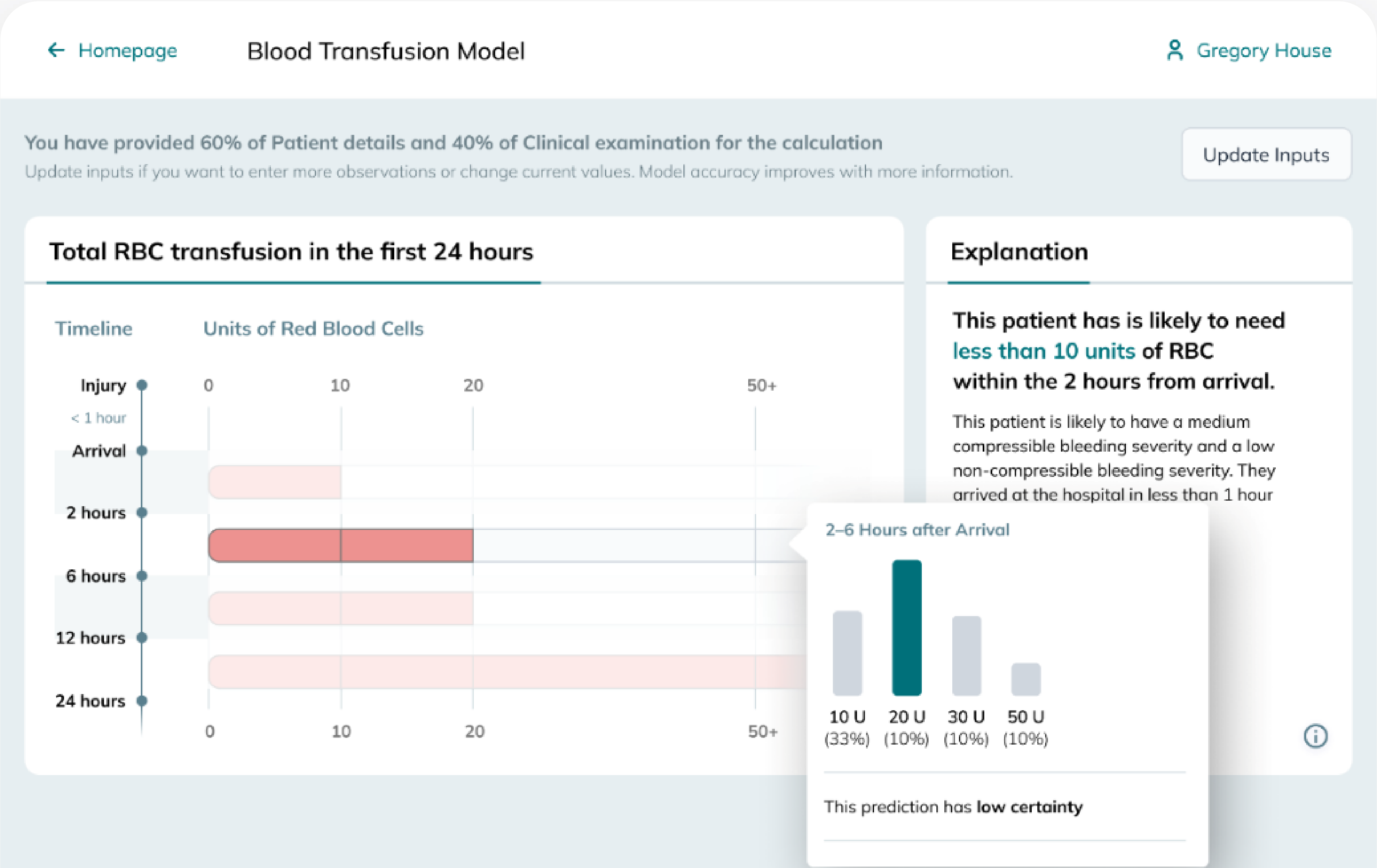
UK Joint Theatre Trauma Registry 2006 to 2014

36,294 units of blood products transfused to 2064 patients



Our work: what is next?

From prediction algorithm to a decision support tool for clinicians



Future Trial

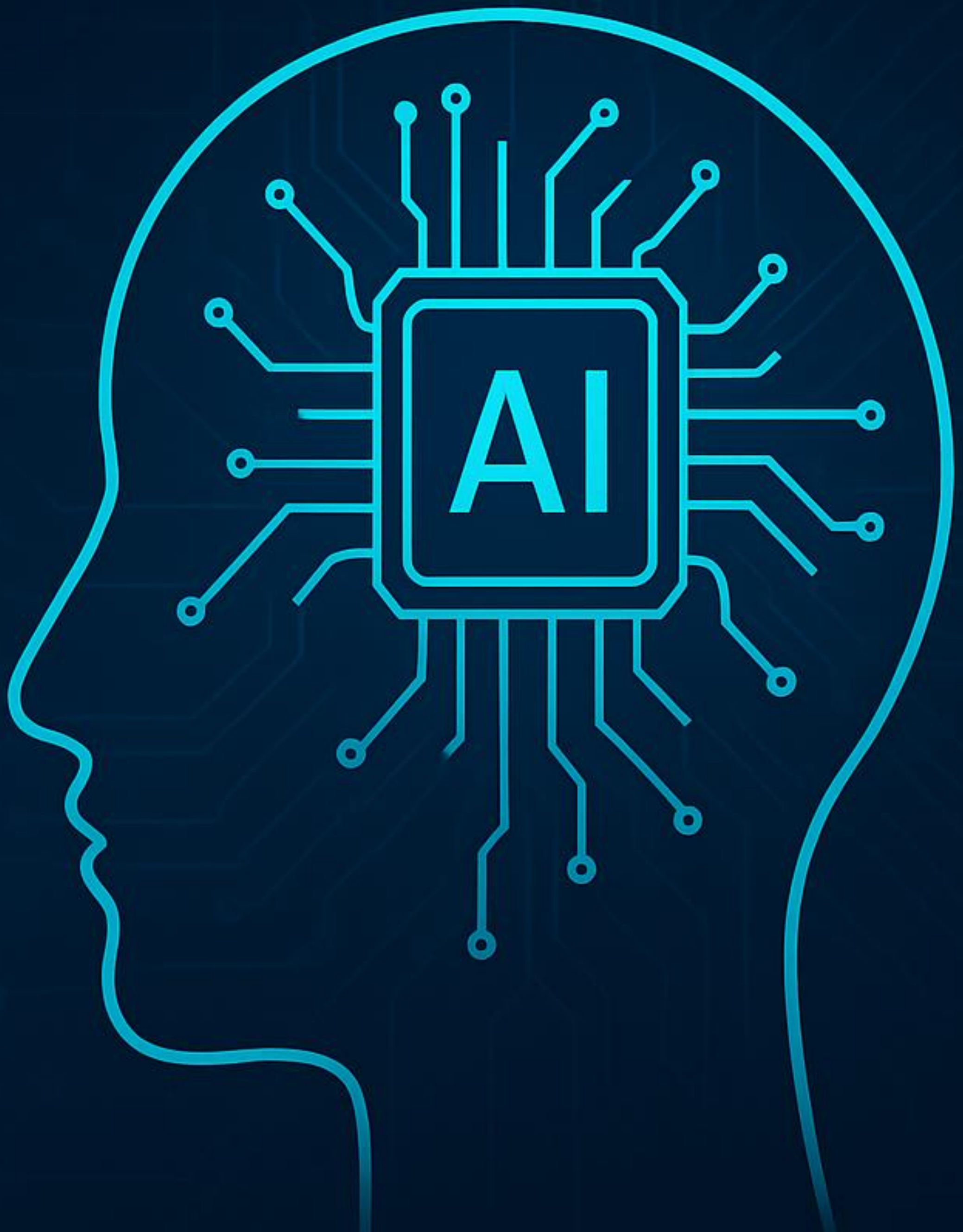


CHaRT
Centre for Healthcare Randomised Trials

London Major Trauma System

CENTRE FOR TRAUMA SCIENCES

1495
UNIVERSITY OF ABERDEEN

Queen Mary
University of London

AI TRiPS

TRAUMA RISK PREDICTION SYSTEM

LONDON AMBULANCE SERVICE

LONDON'S AIR AMBULANCE

NHS
Barts Health
NHS Trust

NHS
Imperial

NHS
King's College Hospital
NHS Foundation Trust

NHS
St George's University Hospitals
NHS Foundation Trust


19:20:13
ZONE 1
Tranexamic Acid
DIFFICULT INTUBATION TROLLEY
PLAN B
PLAN C
ENHANCED AIRWAY
TO BE USED BY THEATRE
STAPLERS
CATHETERS
DOCUMENTATION
CLEAR BAGS
CHECKLIST
BLADES
SMALL SWABS
SHARPS BOXES
MEDIUM SWABS
LIGHT HANDLES
LARGE SWABS
BLUE GAUZE
GALLIPOT
KIDNEY DISH
DRAPES
GENERAL PACK
SMALL DRAPES
SALINE
EYE PROTECTION
MASKS
ANTISEPTIC VIDENE


19:20:13
ZONE 1
AI TRiPS
TRAUMA RISK PREDICTION SYSTEM
TRAUMA SHOCK CALL: ED
Tranexamic Acid
DIFFICULT INTUBATION TROLLEY
TO BE USED BY THEATRE
CODE RED GRATNEL
STAPLERS
DOCUMENTATION
CLEAR BAGS
CHECKLIST
CATHETERS
BLADES
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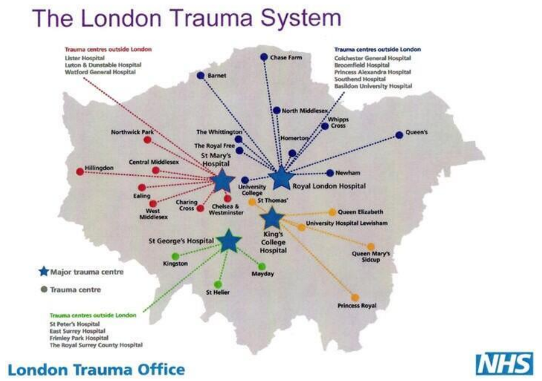
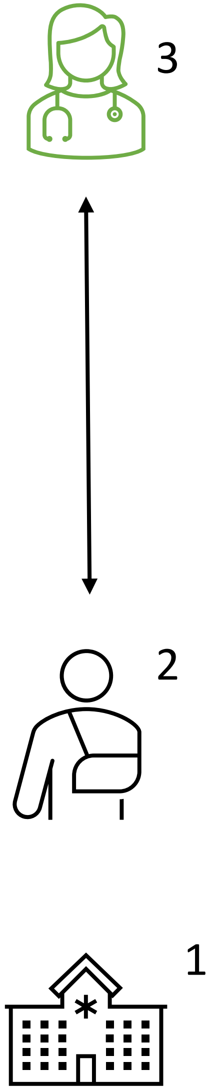
LIGHT HANDLES
MEDIUM SWABS
LARGE SWABS
BLUE GAUZE
GALLIPOT
DRAPES
MASKS
EYE PROTECTION
ANTISEPTIC VIDENE

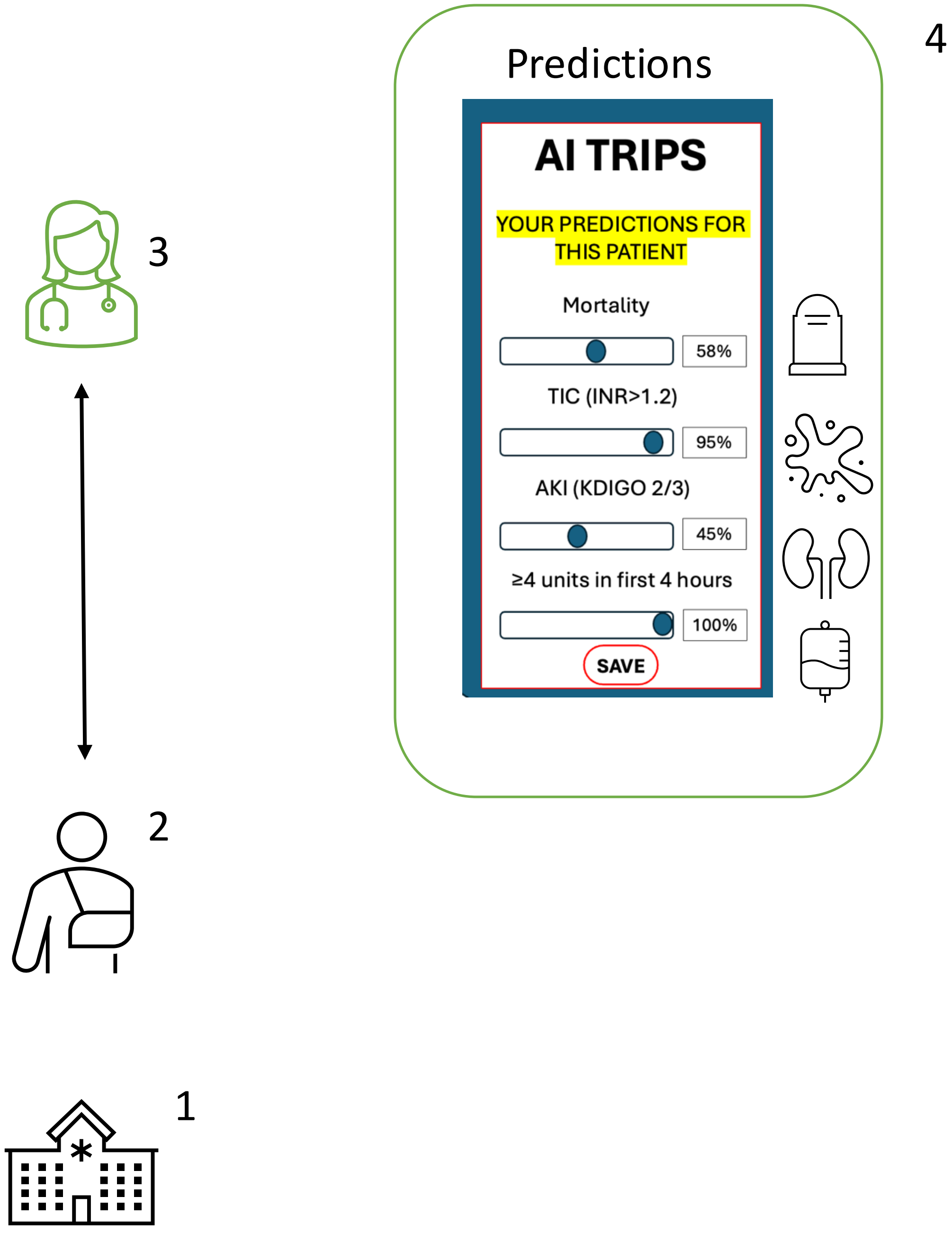
1. Sites: LAA, LAS, KCH, RLH, SMH, SGH



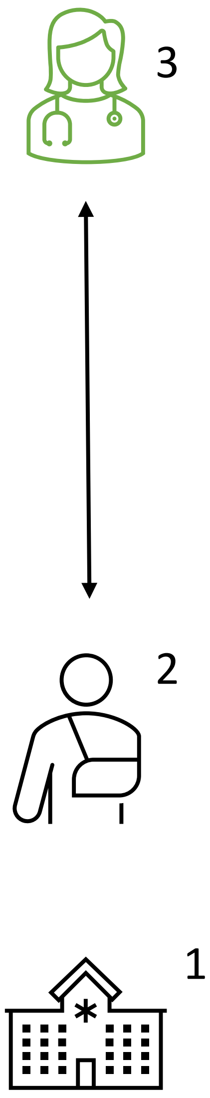
1

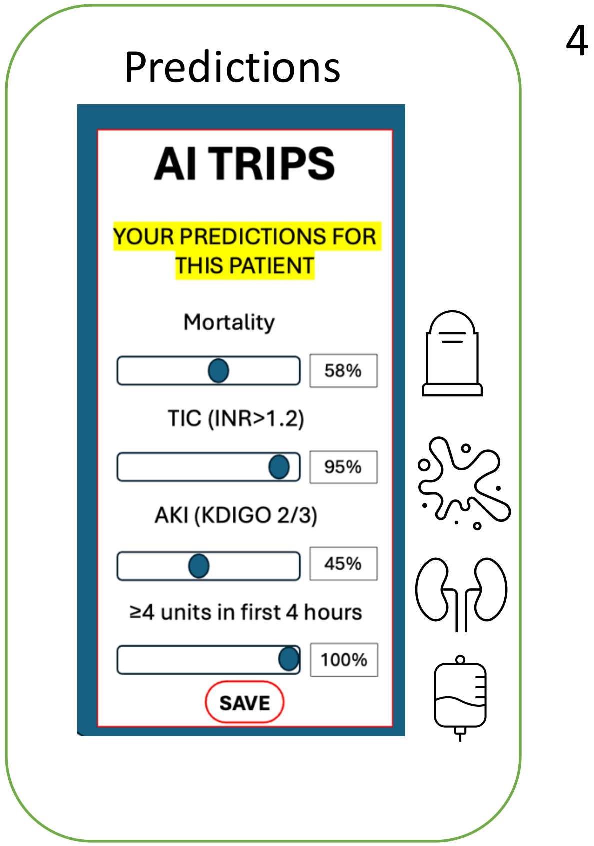


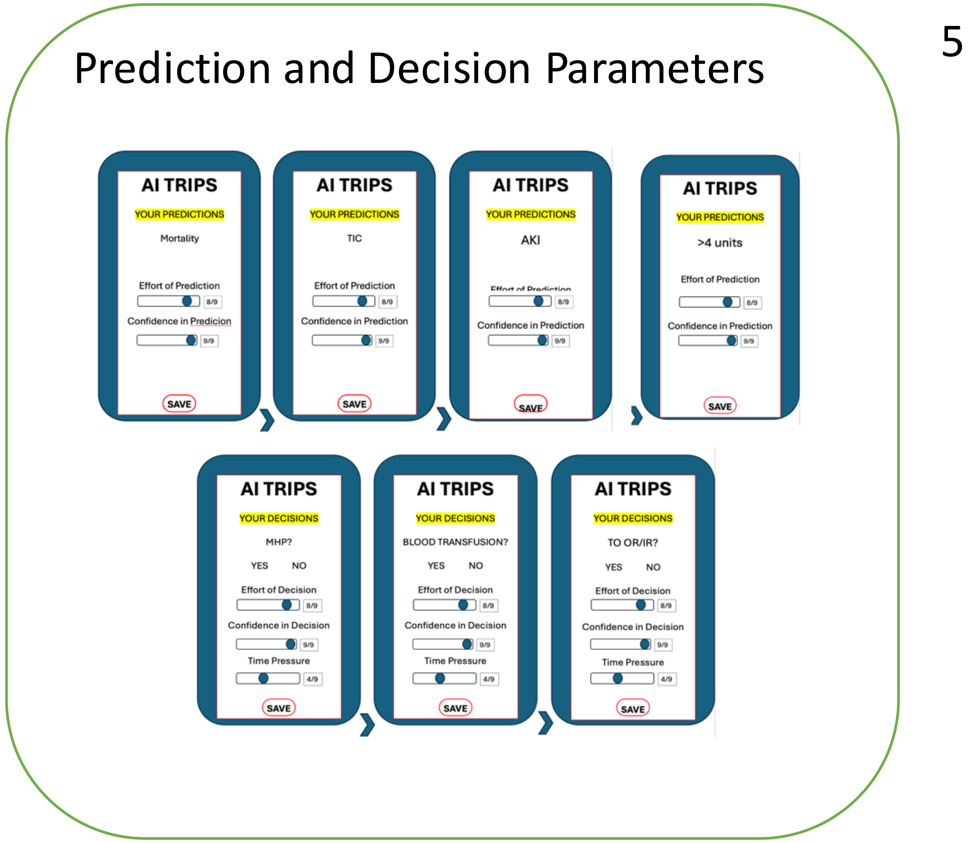
1. Sites: LAA, LAS, KCH, RLH, SMH, SGH
2. Trauma Patients retrieved by LAA and brought to MTC
3. Clinical decision maker in MTC ED



1. Sites: LAA, LAS, KCH, RLH, SMH, SGH
2. Trauma Patients retrieved by LAA and brought to MTC
3. Clinical decision maker in MTC ED
4. Capture of decision-maker predictions (Near Real Time)







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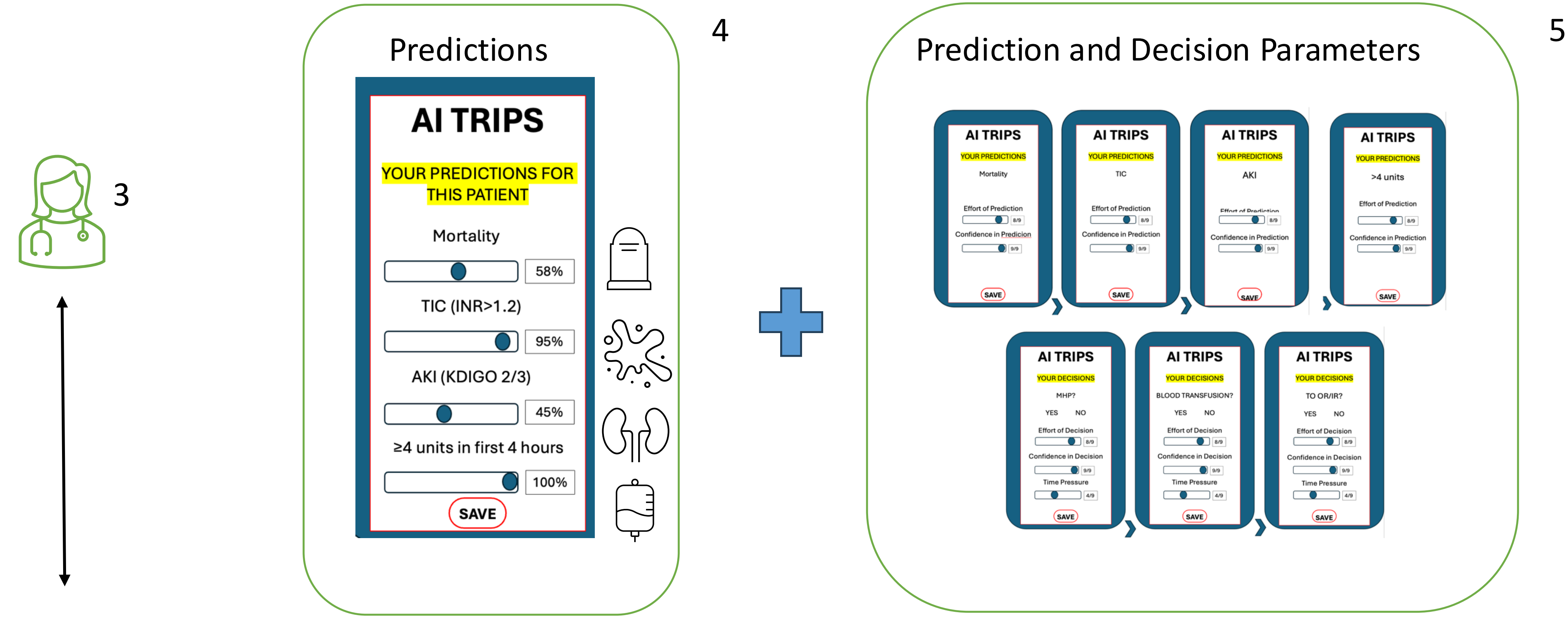
4. Capture of decision-maker predictions (Near Real Time)
5. Capture of prediction and decision parameters (Near Real Time)



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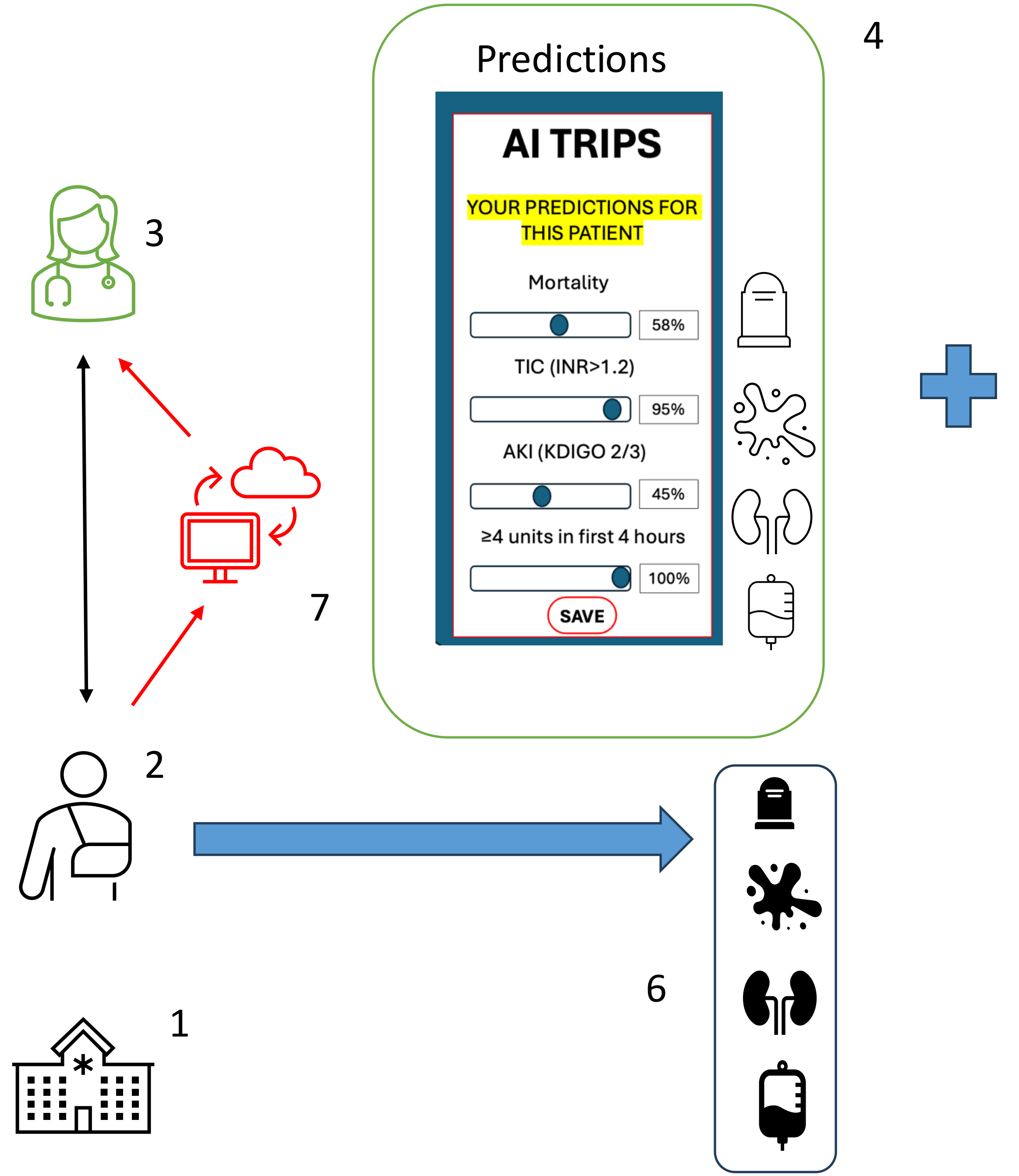
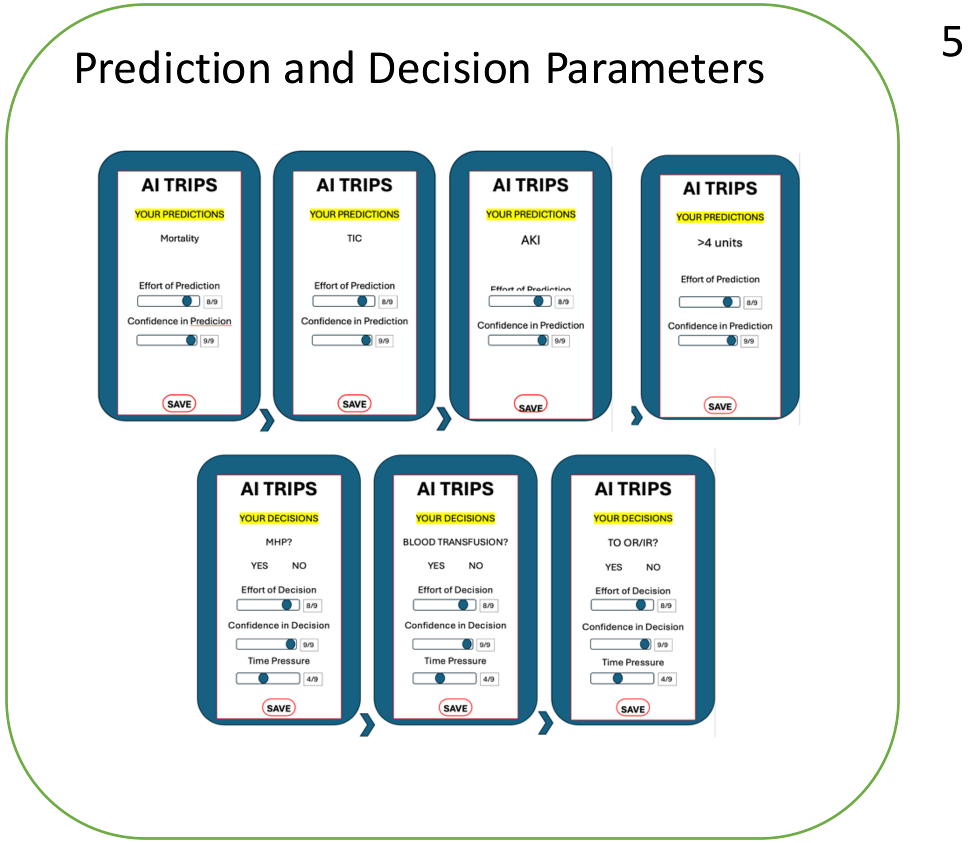
6. Offline capture of patient outcome data from National Major Trauma Registry)





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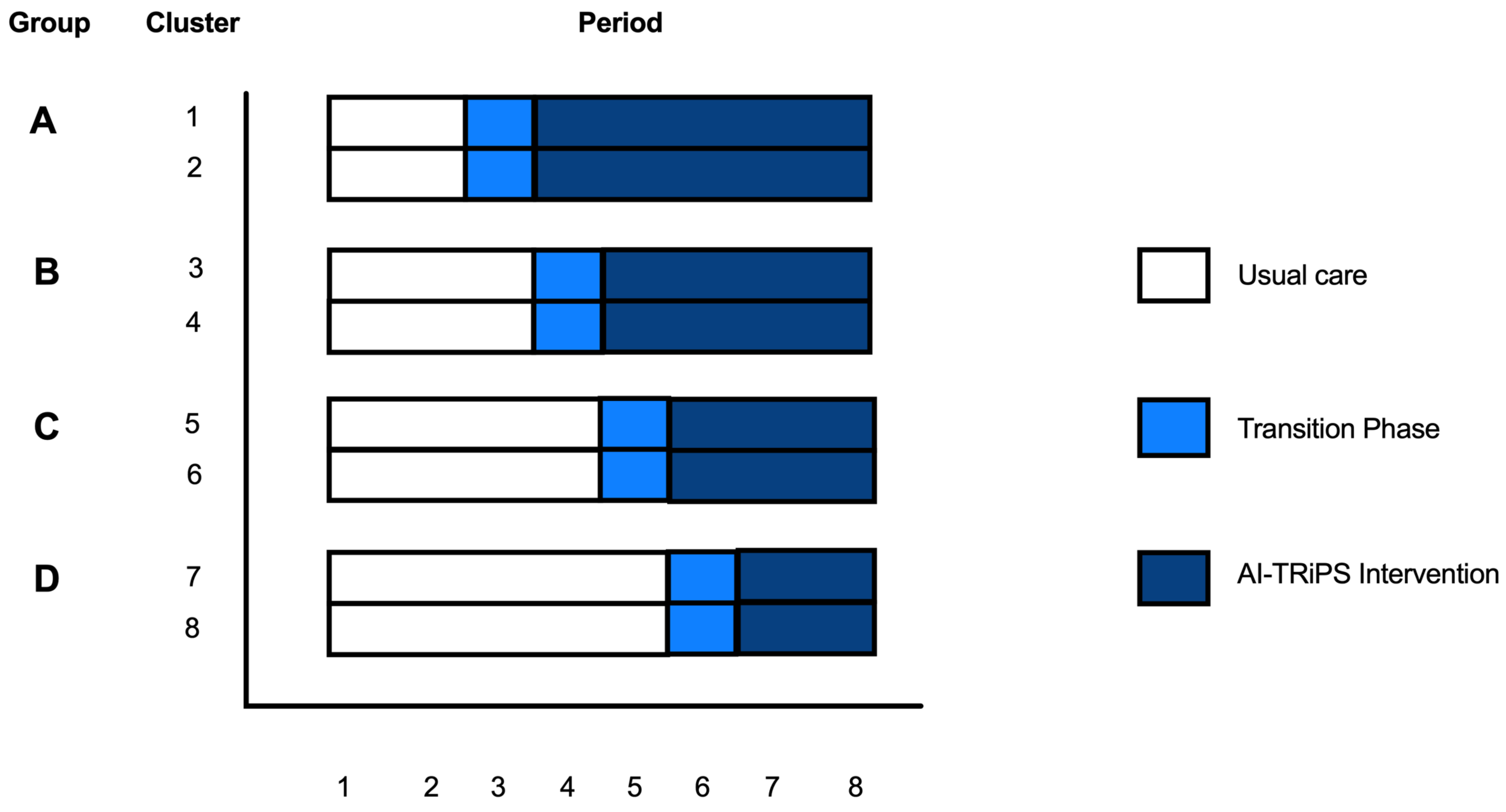
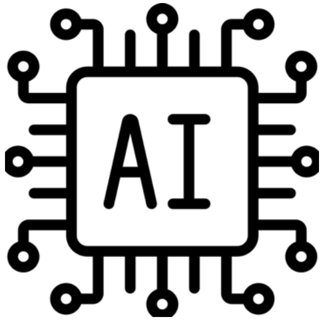
7. Implement AI TRIPS Interface and continue 4/5/6

AI TRiPS
TRAUMA RISK PREDICTION SYSTEM



AI TRiPS
TRAUMA RISK PREDICTION SYSTEM

Advances due to computing **power, data** and **funding**



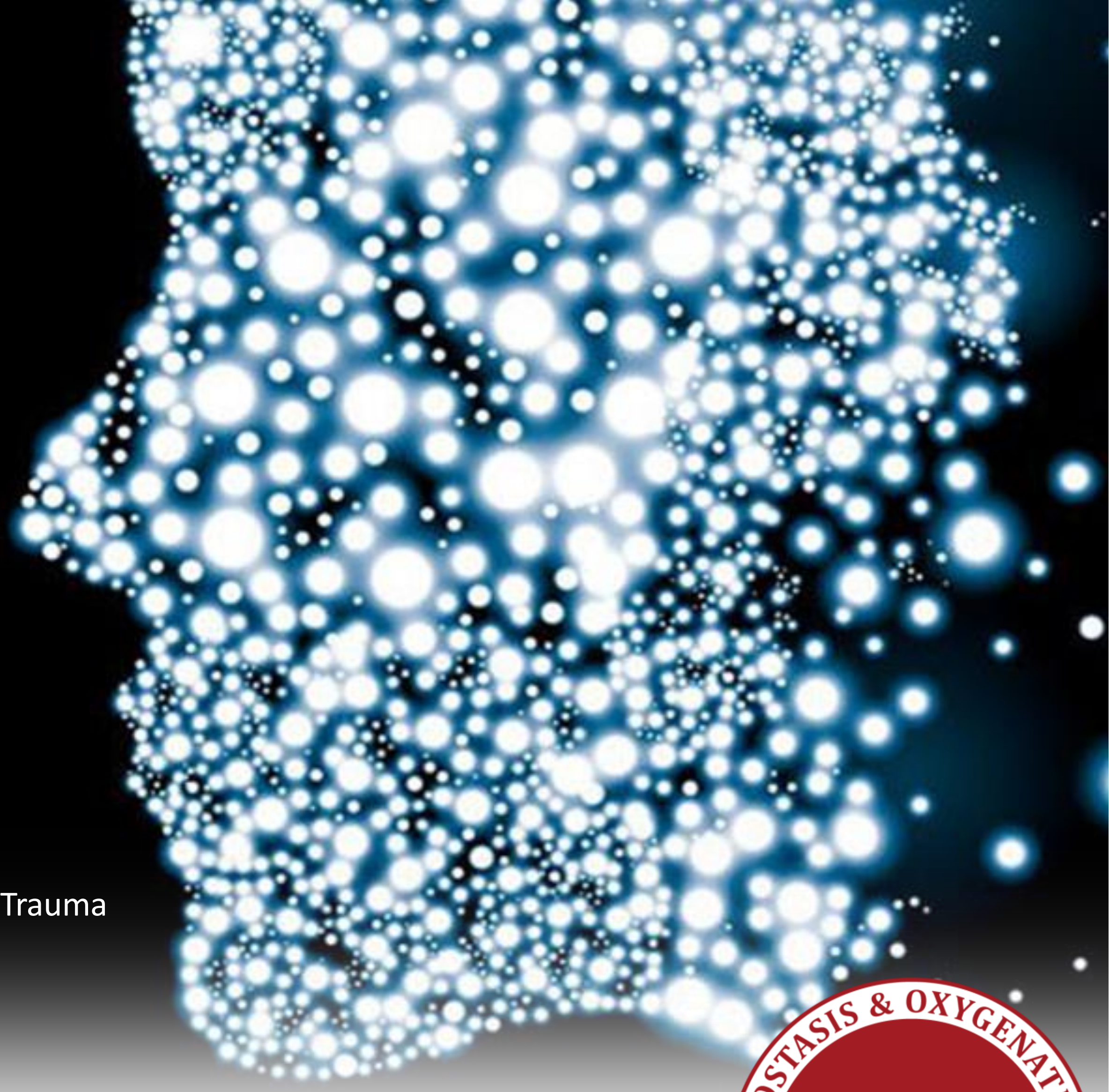
AI is increasingly prevalent

Need evidence to bridge the AI Chasm

Summary

THOR Solstrand Hotel, Norway 19-21st May 2025

Artificial Intelligence: Bleeding



Max Marsden

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Senior Lecturer in Surgical Informatics, Academic Department of Military Surgery and Trauma

DMS Defence Medical Services

CENTRE FOR TRAUMA SCIENCES

LONDON'S AIR AMBULANCE

Queen Mary University of London

TRAUMA HEMOSTASIS & OXYGENATION RESEARCH THOR