TRAUMA
En 2035

TOBIAS GAUSS
Pôle Anesthésie-Réanimation, CHU Grenoble Alpes
Université Grenoble Alpes
Institut des Neurosciences, INSERM U1216, Grenoble

COI

traumabase.eu

TRAUMATRIX

Capgemini invent

LFB BIOMÉDICAMENTS

octapharma

ENJEU	Un environnement conçu
DESIGN/TEAMWORK	Quels design/outils pour vail en équipe?
TECHNOLOGIE	Nouvelles technologiques?
PRODUITS	Quels PSL et nouvelles écules?
IA/DECISION	Analyse signal plexe/support décision
CONCLUSION	

ENJEU

DESIGN TEAM

RCS ADVANCING SURGICAL STANDARDS

TRAUMA SURGERY

Ann R Coll Surg Engl 2015; **97:** 262–268
doi 10.1308/003588414X14055925060875

Human factors in decision making in major trauma in Camp Bastion, Afghanistan

GS Arul[1], HEJ Pugh[2], SJ Mercer[3], MJ Midwinter[4]

[1]212 Field Hospital, Sheffield, UK
[2]16 Medical Regiment, Colchester, UK
[3]Aintree University Hospital NHS Foundation Trust, UK
[4]Royal Centre for Defence Medicine, Birmingham, UK

DESIGN TEAM

European Journal of Trauma and Emergency Surgery (2021) 47:1847–1852
https://doi.org/10.1007/s00068-020-01374-5

ORIGINAL ARTICLE

Dual-room twin-CT scanner in multiple trauma care: first results after implementation in a level one trauma centre

Maximilian Kippnich[1] · Nora Schorscher[1] · Markus Kredel[2] · Christian Markus[2] · Lars Eden[3] · Tobias Gassenmaier[4] · Johann Lock[5] · Thomas Wurmb[1]

DESIGN TEAM

ORIGINAL ARTICLE

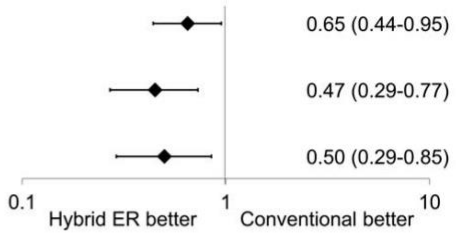
OPEN

The Survival Benefit of a Novel Trauma Workflow that Includes Immediate Whole-body Computed Tomography, Surgery, and Interventional Radiology, All in One Trauma Resuscitation Room

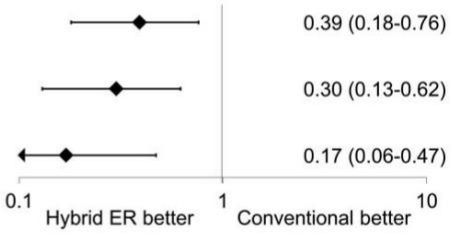
A Retrospective Historical Control Study

Takahiro Kinoshita, MD, Kazuma Yamakawa, MD, PhD,* Hiroki Matsuda, MD,* Yoshiaki Yoshikawa, MD,* Daiki Wada, MD, PhD,† Toshimitsu Hamasaki, PhD,‡ Kota Ono, MPH,§ Yasushi Nakamori, MD, PhD,† and Satoshi Fujimi, MD, PhD**

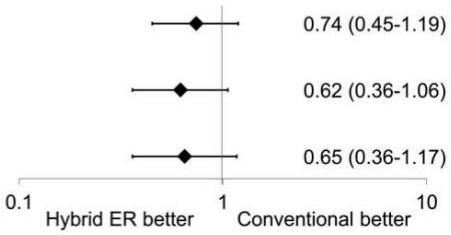
28-day mortality	Conventional vs. Hybrid ER	Conventional n (%)	Hybrid ER n (%)	OR (95% CI)
Unadjusted	360 vs. 336	78 (22%)	51 (15%)	0.65 (0.44-0.95)
Ps adjusted				0.47 (0.29-0.77)
Multivariable				0.50 (0.29-0.85)



Death from exsanguination	Conventional vs. Hybrid ER	Conventional n (%)	Hybrid ER n (%)	OR (95% CI)
Unadjusted	360 vs. 336	29 (8%)	11 (3%)	0.39 (0.18-0.76)
Ps adjusted				0.30 (0.13-0.62)
Multivariable				0.17 (0.06-0.47)



Death from TBI	Conventional vs. Hybrid ER	Conventional n (%)	Hybrid ER n (%)	OR (95% CI)
Unadjusted	360 vs. 336	45 (13%)	32 (10%)	0.74 (0.45-1.19)
Ps adjusted				0.62 (0.36-1.06)
Multivariable				0.65 (0.36-1.17)



DESIGN TEAM

Diane Dechoc

DESIGN TEAM

AAST PODIUM 2023

Getting out of the bay faster: Assessing trauma team performance using trauma video review

Maiga, Amelia W. MD, MPH; Vella, Michael A. MD, MBA; Appelbaum, Rachel D. MD; Irlmeier, Rebecca MS; Ye, Fei PhD, MSPH; Holena, Daniel N. MD, MSCE; Dumas, Ryan P. MD; the TVRC Investigators

Collaborators

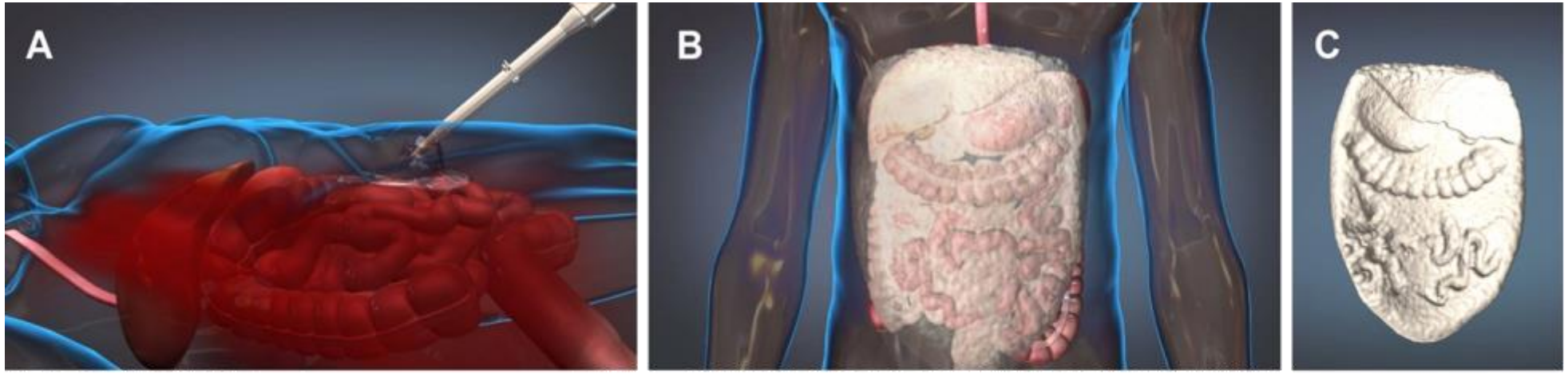

TECH

TECH


Flat Free
Flat Preventative And Permanent Tire Sealant for Over-the-Road, High-Speed Vehicles


vittoria

TECH



Injury occurs and ResQFoam deployed

ResQFoam forms *in situ*

ResQFoam surgically extracted

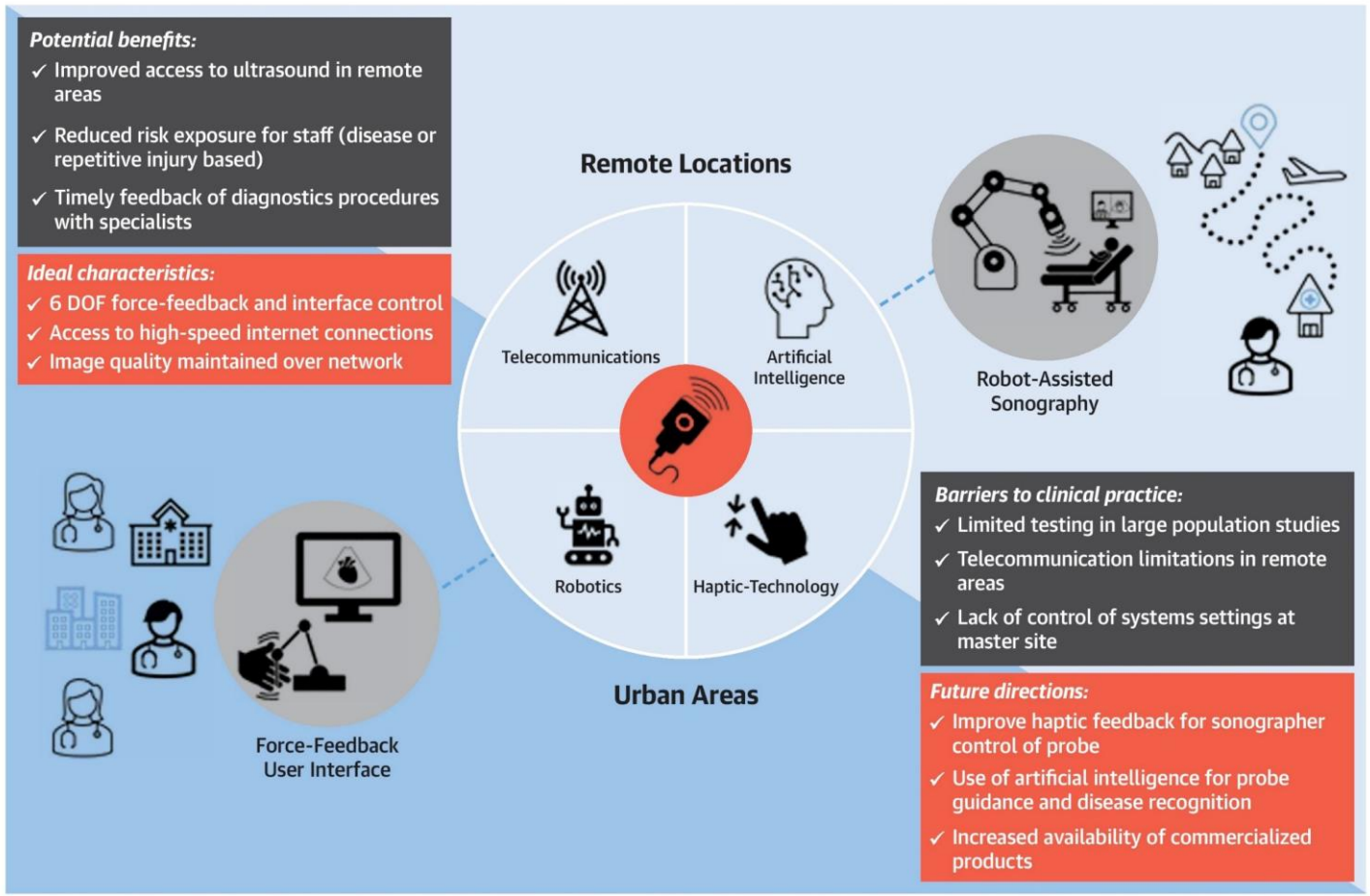
Open access Original research

Trauma Surgery & Acute Care Open

Self-expanding foam injected into the peritoneal space improves survival in a model of complex pelvic fracture and retroperitoneal exsanguination

Quynh P Pham ,[1] John O Hwabejire,[2] Ahmed E Elsharkawy,[2,3] Ahmed I Eid ,[2,3] Michael J Duggan,[2] Shawn Gelsinger,[1] Michael Fornaciari,[1] Upma Sharma,[1] David R King [4]

CENTRAL ILLUSTRATION: Benefits and Barriers to Clinical Use of Robotic-Assisted Ultrasound



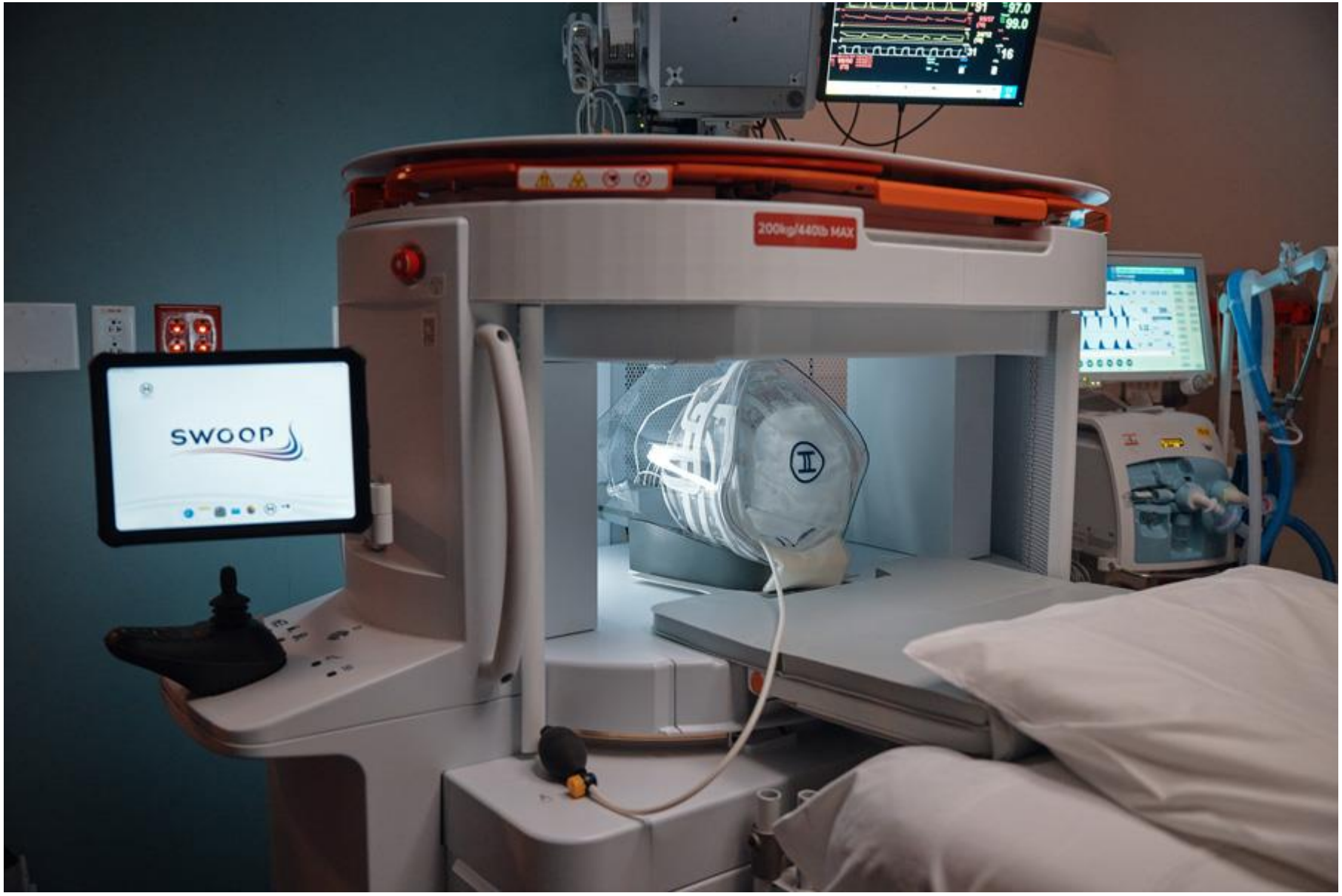
Hidalgo EM, et al. J Am Coll Cardiol Img. 2023;16(2):239-247.

Published in final edited form as:
Emerg Radiol. 2023 June ; 30(3): 251–265. doi:10.1007/s10140-023-02120-1.

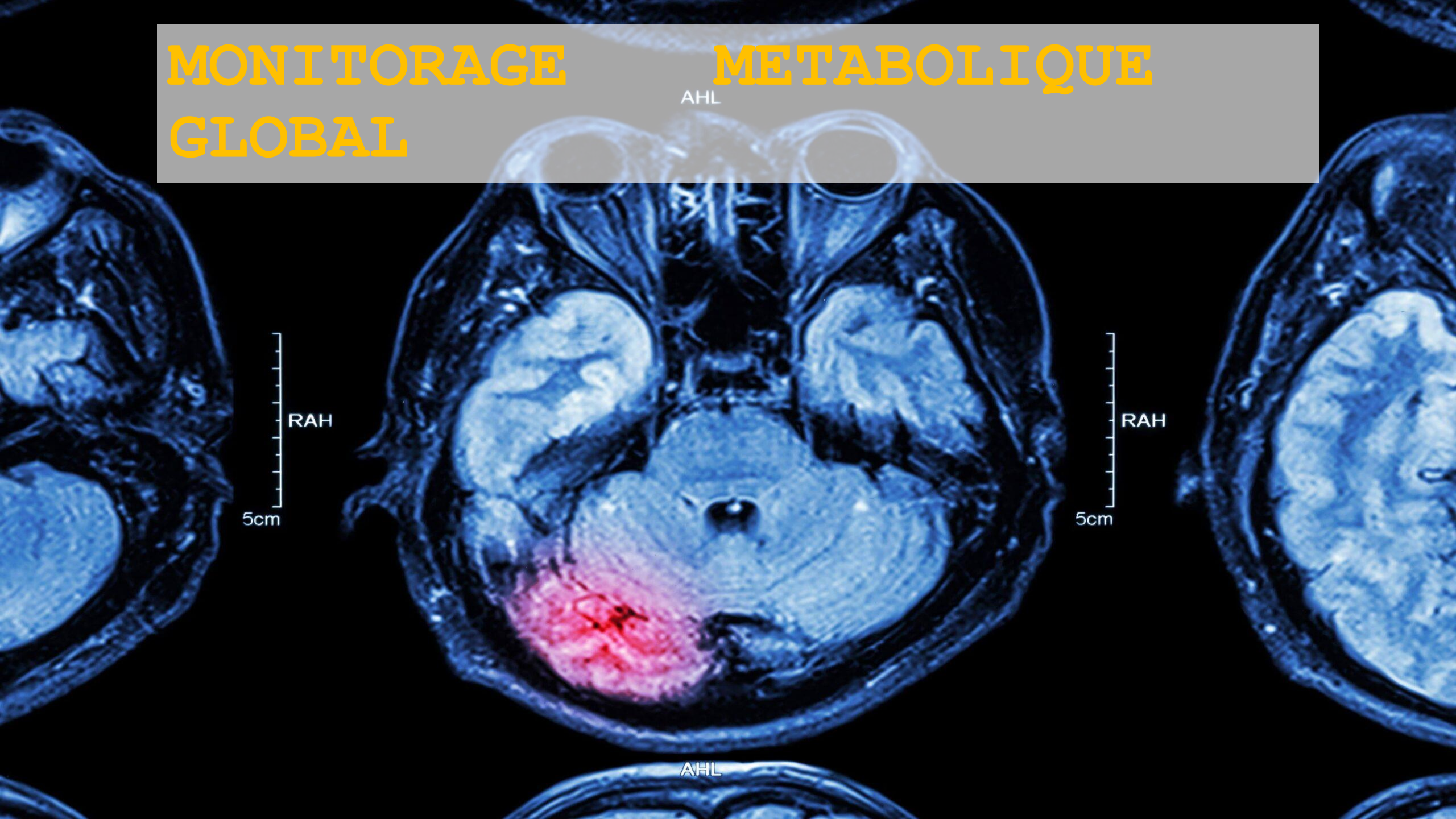
Artificial intelligence CAD tools in trauma imaging: a scoping review from the American Society of Emergency Radiology (ASER) AI/ML Expert Panel

David Dreizin[1], Pedro V. Staziaki[2], Garvit D. Khatri[3], Nicholas M. Beckmann[4], Zhaoyong Feng[5], Yuanyuan Liang[5], Zachary S. Delproposto[6], Maximiliano Klug[7], J. Stephen Spann[8], Nathan Sarkar[9], Yunting Fu[10]

TECH



MONITORAGE METABOLIQUE GLOBAL



Molecular and Cellular Biochemistry (2025) 480:2797–2814
https://doi.org/10.1007/s11010-024-05176-w

Efficacy of biomarkers and imaging techniques for the diagnosis of traumatic brain injury: challenges and opportunities

James Duerksen[1] · Rhea Carina T. Lopez[1] · Paramjit S. Tappia[1] · Bram Ramjiawan[1,2] · Behzad Mansouri[3]

Table 3 Novel imaging techniques for diagnosing mTBI along with specific domains of assessment. Benefits and limitations for each technique are included

Imaging technique	Domains assessed	Benefits	Limitations
Diffusion Tensor Imaging (DTI)	Examines white matter by measuring the diffusion of water in the brain [100]	Detects microstructural damage in the brain [100]	Sensitivity is not well known [100] Cannot distinguish between axons, myelin, microtubules, etc. [153]
Susceptibility Weighted Imaging (SWI)	Detects microhemorrhages in the brain [100]	Highly sensitive to microhemorrhage [100] Can detect abnormalities even after symptom resolution [154]	Only detects microhemorrhage. Is not sensitive to any other concussion-related disturbances [100]
Magnetic Resonance Spectroscopy (MRS)	Assesses brain metabolism by developing signals of metabolites [100]	Provides valuable information about numerous brain metabolites involved in concussion Could also help develop a deeper understanding of pathophysiology [100]	Inconsistent results [100]
Blood-Oxygen Level Dependent fMRI (BOLD-fMRI)	Detects changes in cerebral blood flow by measuring variations in blood oxygenation [100]	Good predictor of recovery, even in the absence of symptoms [151] Can be task-based or resting-state [100]	Highly sensitive to external distractors such as head movement [100] Conflicting results in task-based studies [155, 156]
Arterial Spin Labelling (ASL)	Labels arterial blood flow to the brain to measure blood perfusion [100]	Alterations in ASL-derived cerebral blood flow correlate with symptom pattern, severity, and cognitive performance Can detect abnormalities after symptom resolution [100]	Limited published evidence [100]
Magnetoencephalography	Measures local magnetic fluctuations in the brain as a result of postsynaptic electric currents [30]	High temporal resolution [157] High sensitivity [157]	Poor spatial resolution Expensive and require specialized knowledge for analysis Poor specificity [157]


PRODUITS

PRODUITS

Home | JAMA Surgery | Vol. 155, No. 2

Original Investigation FRE

Timing to First Whole Blood Transfusion and Survival Following Severe Hemorrhage in Trauma Patients

Crisanto M. Torres, MD, MPH[1]; Kelly M. Kenzik, PhD[1]; Noelle N. Saillant, MD[1]; et al

» Author Affiliations | Article Information

Original Investigation ONLINE ONLY FREE

Association of Prehospital Plasma Transfusion With Survival in Trauma Patients With Hemorrhagic Shock When Transport Times Are Longer Than 20 Minutes

A Post Hoc Analysis of the PAMPer and COMBAT Clinical Trials

Anthony E. Pusateri, PhD[1]; Ernest E. Moore, MD[2]; Hunter B. Moore, MD, PhD[2]; et al

Details

Science
Volume 385, Issue 6704
Jul 2024

ARTICLE

There will be blood

View article page

Andrew Zaleski

https://doi.org/10.1126/science.adr4067

Publisher	American Association for the Advancement of Science
ISSN	0036-8075
eISSN	1095-9203
Published in	July 5, 2024

FEATURES

THERE WILL BE BLOOD

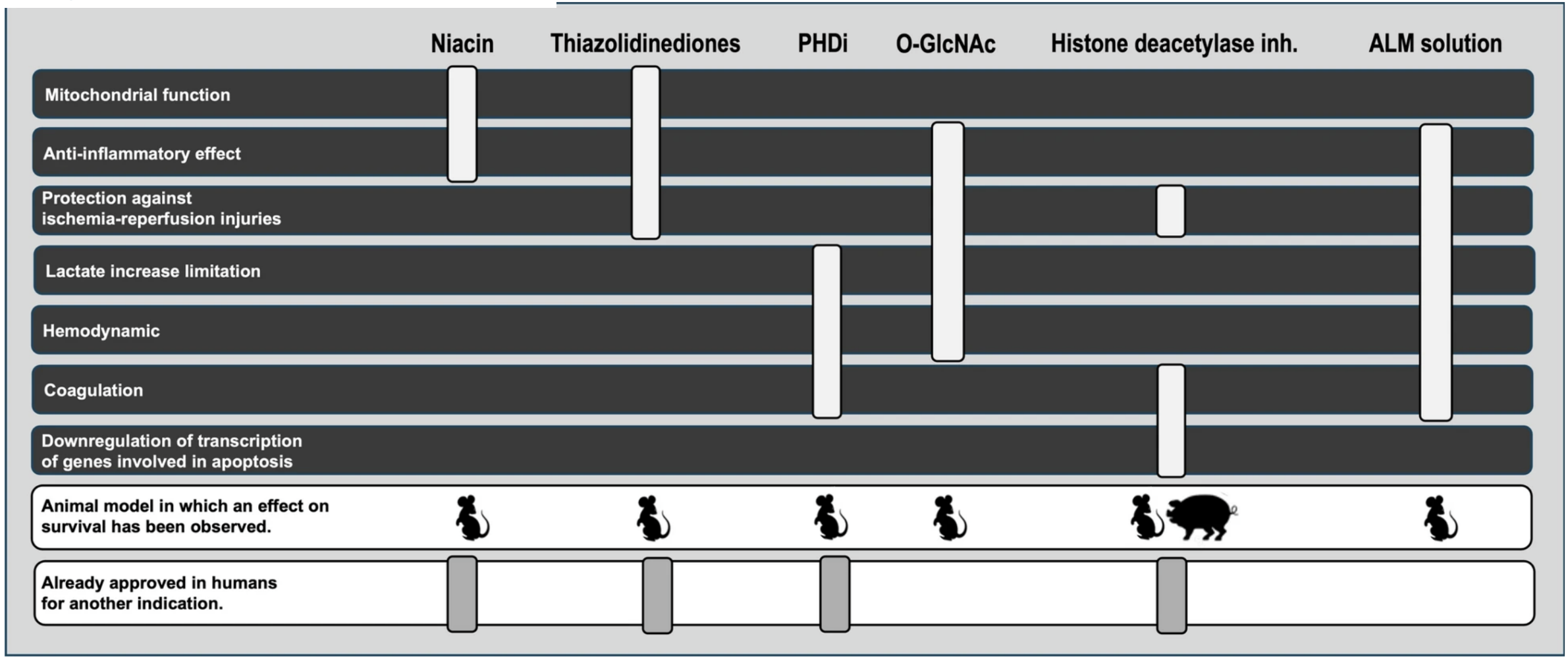
Is mimicking the cells that carry hemoglobin the key to a blood substitute?

By **Andrew Zaleski**
Photography by **Matt Roth**

Review | Open access | Published: 29 March 2025

Adjuvant therapies for management of hemorrhagic shock: a narrative review

Yann Daniel, Frédérique Dufour-Gaume, Amandine Vergnaud, Manon Denis, Louise Giaume, Bertrand Rozec, Nicolas Prat & Benjamin Lauzier



Schematic representation of the potential modes of action of the different molecules according to the pre-clinical data obtained in animals. PHDi, prolyl hydroxylase domain inhibitors; O-GlcNAc, O-GlcNAcylation; Histone deacetylase inh, histone deacetylase inhibitors; ALM solution, adenosine–lidocaine–magnesium solution

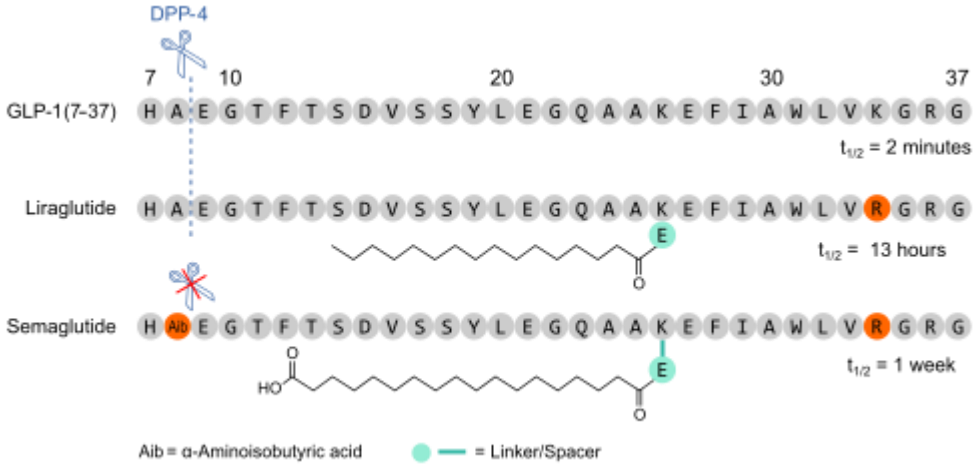
Target	Compound/intervention	References
Oxygen carriers	Human hemoglobin	[87, 88]
	Perfluorocarbons	[89]
Platelet dysfunction	Anti-HMGB-1	[90]
	Synthetic platelet (particles)	[91, 92]
	Cold or frozen platelets	[93]
	Platelet vesicles	[94]
Endothelial permeability	rhADAMTS13	[95]
	Plasma	[95]
	Albumin	[96]
	Tyrosine kinase inhibitors	[97]
	Vasculotide	[98]
	Heparan sulfate	[99]
	Antithrombin	[100]
	Adiponectin	[101]
	(Vesicles from) stem cells	[102]
Overshoot damage molecules	Hexadimethrine bromide	[103]
	DNAse-1	[104]
Overshoot inflammation	JAK inhibitor Baricitinib	[105]
	Macrophage migration inhibitor ISO-1	[106]
	Lipid mediator Resolvin D1	[107]
	NADPH oxidase inhibitor diphenylene iodonium	[108]
	Complement activation inhibitor nomacopan	[109]
Hormones	Estrogen	[110]
Blood purification techniques	Hemoadsorption	[111]

Perspective | Open access | Published: 13 February 2024

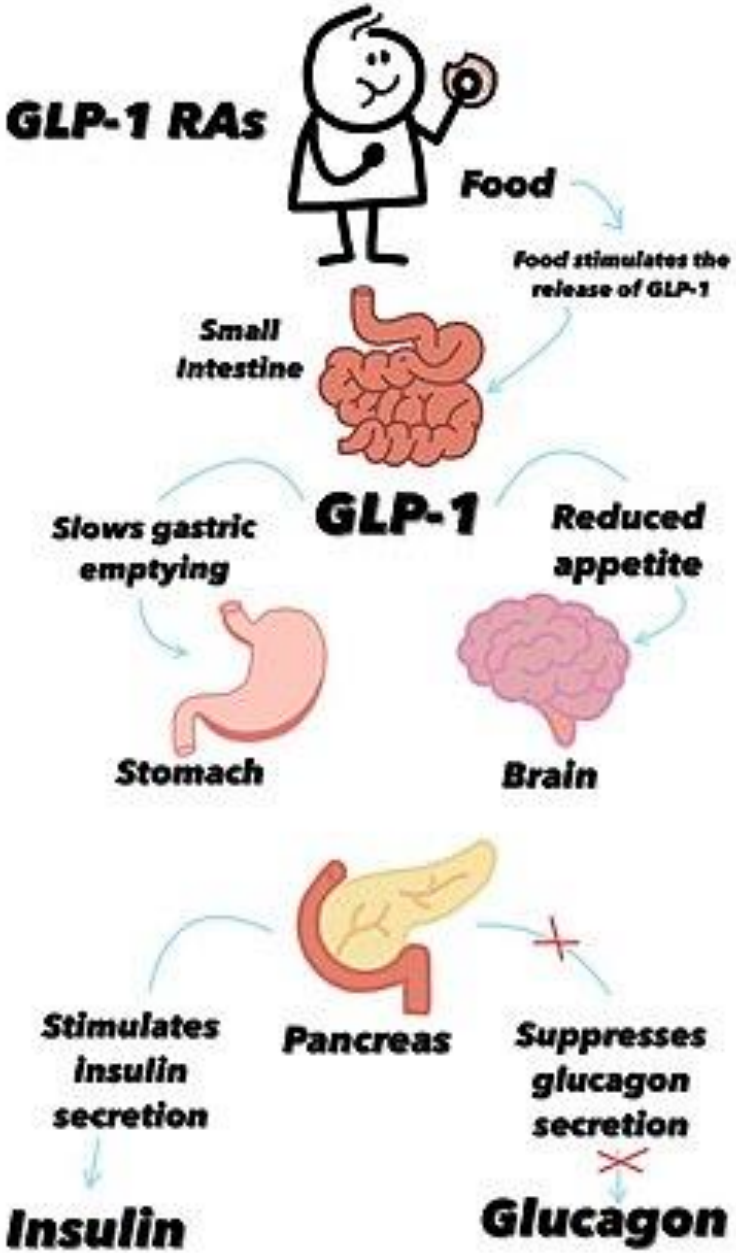
Transforming research to improve therapies for trauma in the twenty-first century

Nicole P. Juffermans ✉, Tarik Gözden, Karim Brohi, Ross Davenport, Jason P. Acker, Michael C. Reade, Marc Maegele, Matthew D. Neal & Philip C. Spinella

Critical Care **28**, Article number: 45 (2024) | Cite this article


DPP-4
7
10
20
30
37
GLP-1(7-37)
H A E G T F T S D V S S Y L E G Q A A K E F I A W L V K G R G
t1/2 = 2 minutes
Liraglutide
H A E G T F T S D V S S Y L E G Q A A K E F I A W L V R G R G
E
t1/2 = 13 hours
Semaglutide
H Aib E G T F T S D V S S Y L E G Q A A K E F I A W L V R G R G
HO
E
t1/2 = 1 week
Aib = α-Aminoisobutyric acid
= Linker/Spacer


PRESCRIPTION ONLY MEDICINE
KEEP OUT OF REACH OF CHILDREN
OZEMPIC
semaglutide (rys)
Ozempic® pre-filled pen
2 mg semaglutide
solution for injection
subcutaneous use
1.5 mL
OZEMPIC
semaglutide (rys)

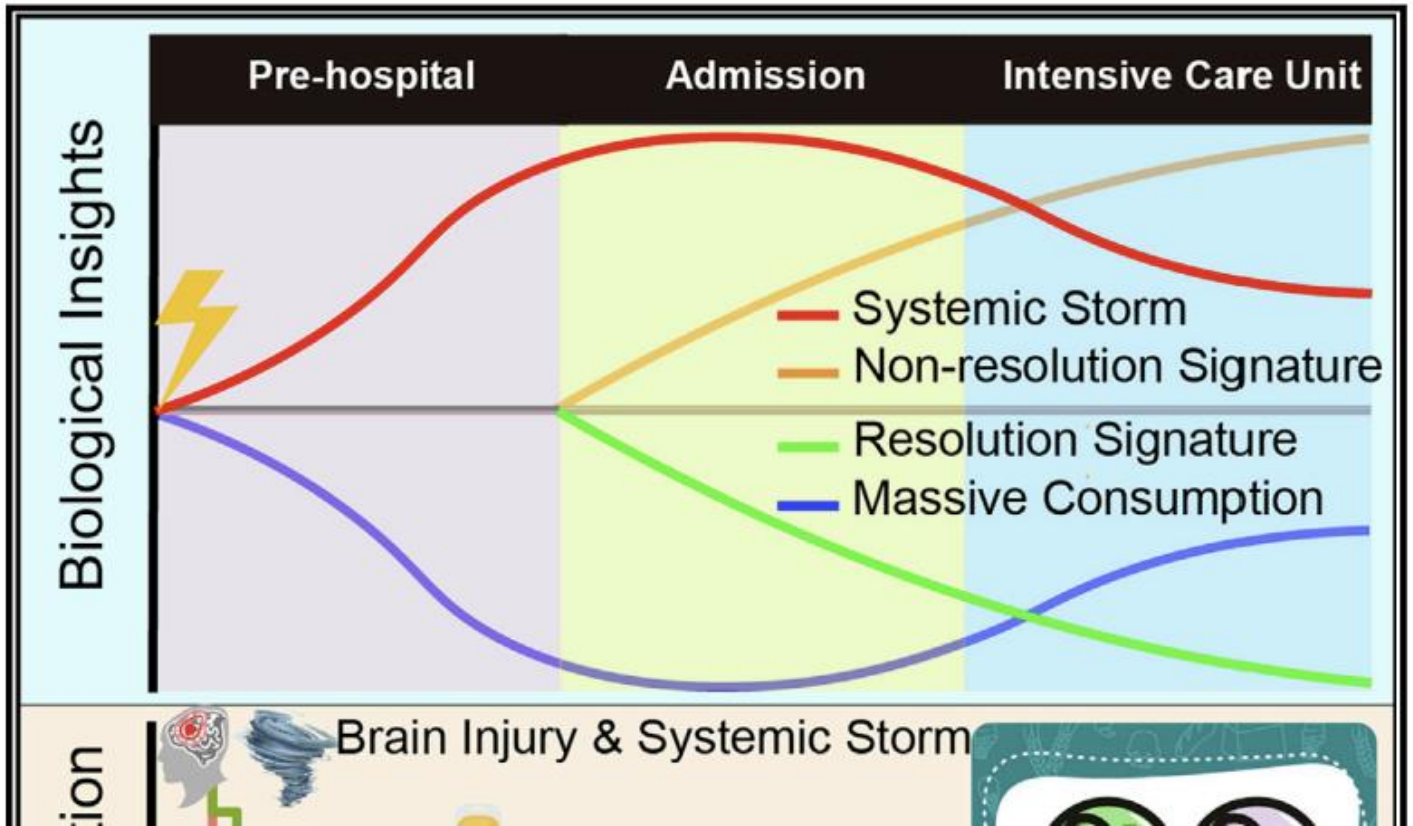

GLP-1 RAs
Food
Food stimulates the release of GLP-1
Small Intestine
GLP-1
Slows gastric emptying
Reduced appetite
Stomach
Brain
Pancreas
Stimulates insulin secretion
Suppresses glucagon secretion
Insulin
Glucagon

Cell Reports
Medicine

Article

Multi-omic analysis in injured humans: Patterns align with outcomes and treatment responses

Graphical abstract



Authors

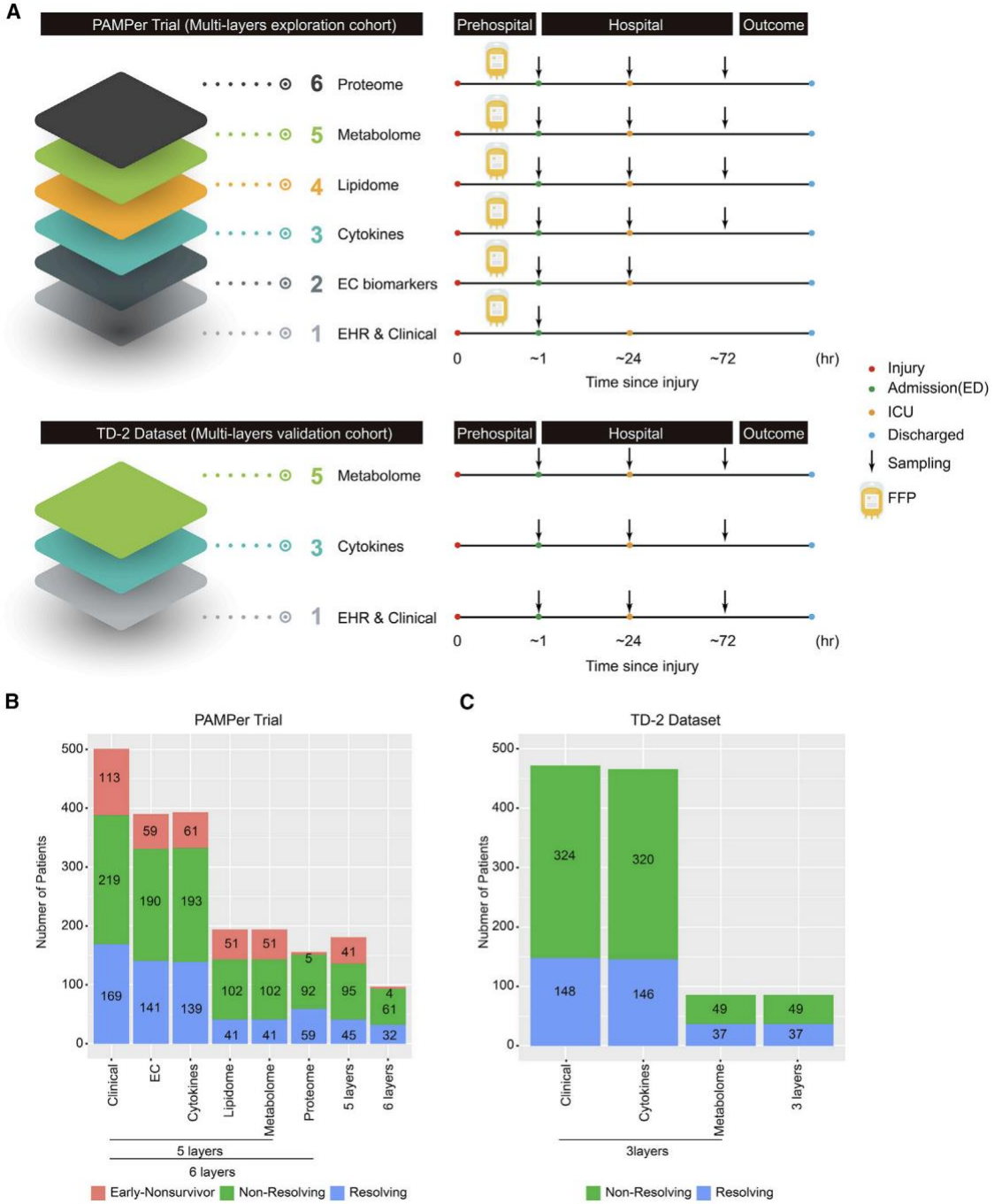
Junru Wu, Yoram Vodovotz, Sultan Abdelhamid, ..., Jason L. Sperry, Timothy R. Billiar, PAMPer study group

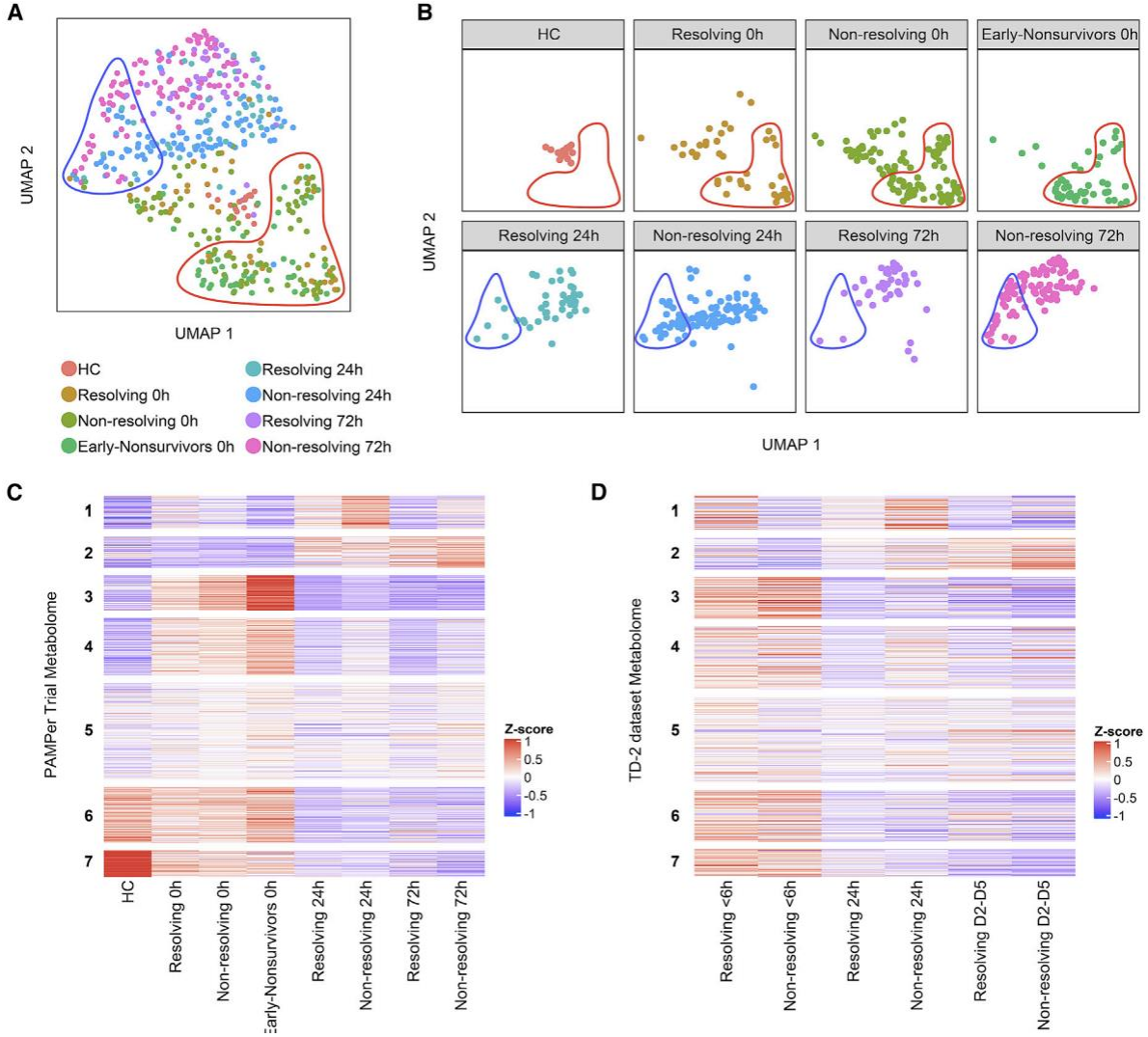
Correspondence

nealm2@upmc.edu (M.D.N.), sperryjl@upmc.edu (J.L.S.), billiartr@upmc.edu (T.R.B.)

In brief

Wu et al. report a longitudinal multi-omic analysis of the circulation in trauma patients. Cross-platform data integration


A
PAMPer Trial (Multi-layers exploration cohort)
Prehospital
Hospital
Outcome
6 Proteome
5 Metabolome
4 Lipidome
3 Cytokines
2 EC biomarkers
1 EHR & Clinical
0
~1
~24
~72
(hr)
Time since injury
Injury
Admission(ED)
ICU
Discharged
Sampling
FFP
TD-2 Dataset (Multi-layers validation cohort)
5 Metabolome
3 Cytokines
1 EHR & Clinical
B
PAMPer Trial
Nubmer of Patients
113
59
61
219
190
193
169
141
139
51
51
102
102
41
41
5
92
59
41
95
45
4
61
32
Clinical
EC
Cytokines
Lipidome
Metabolome
Proteome
5 layers
6 layers
5 layers
6 layers
Early-Nonsurvivor
Non-Resolving
Resolving
C
TD-2 Dataset
324
320
148
146
49
49
37
37
Clinical
Cytokines
Metabolome
3 layers
3layers
Non-Resolving
Resolving


A
UMAP 2
UMAP 1
HC
Resolving 0h
Non-resolving 0h
Early-Nonsurvivors 0h
Resolving 24h
Non-resolving 24h
Resolving 72h
Non-resolving 72h
B
HC
Resolving 0h
Non-resolving 0h
Early-Nonsurvivors 0h
Resolving 24h
Non-resolving 24h
Resolving 72h
Non-resolving 72h
UMAP 2
UMAP 1
C
PAMPer Trial Metabolome
Z-score
HC
Resolving 0h
Non-resolving 0h
Early-Nonsurvivors 0h
Resolving 24h
Non-resolving 24h
Resolving 72h
Non-resolving 72h
D
TD-2 dataset Metabolome
Z-score
Resolving <6h
Non-resolving <6h
Resolving 24h
Non-resolving 24h
Resolving D2-D5
Non-resolving D2-D5

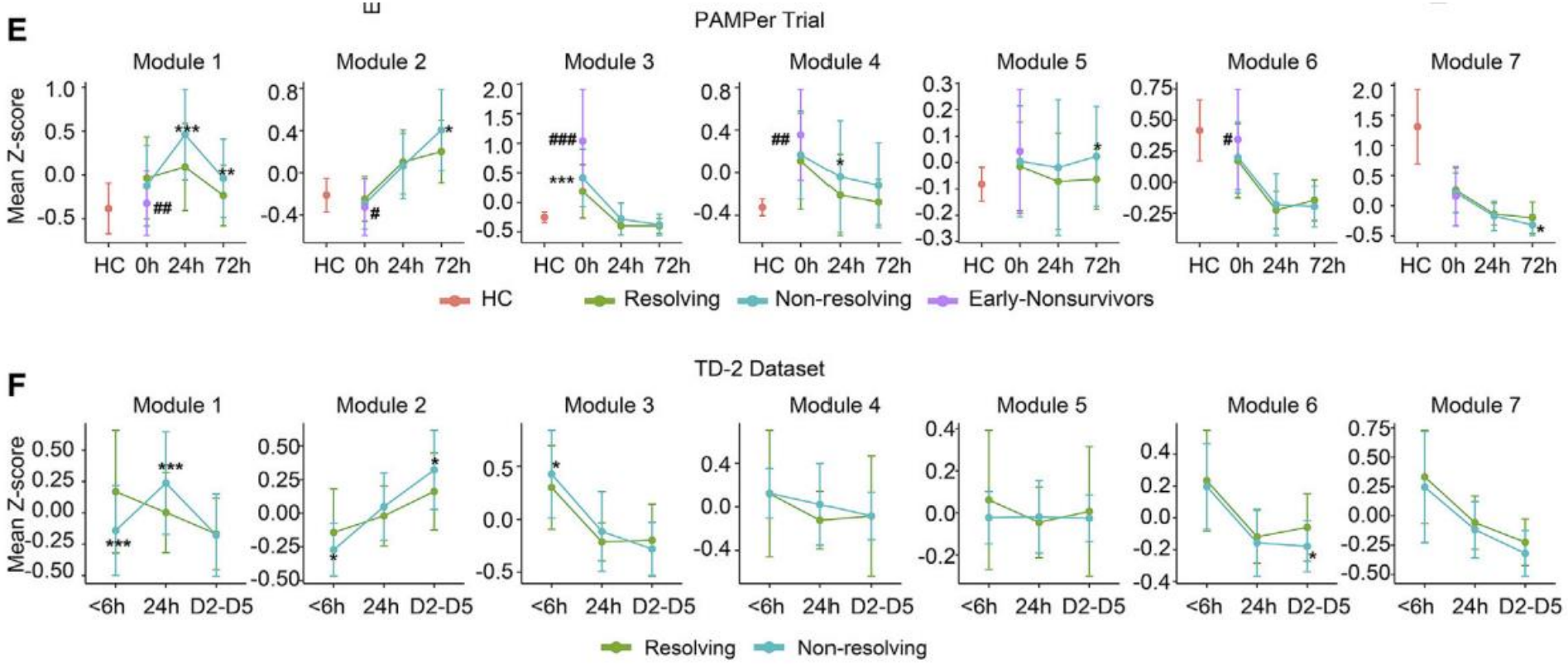


Figure 2. Global temporal patterns within the circulating metabolome based on patient outcomes

(A and B) Uniform manifold approximation and projection (UMAP) plots show the distribution of healthy controls (HCs; n = 17) and patients with trauma (n = 194). All subjects (A) and separated by time and outcome (B). Numbers of subjects in each group: 17 (HCs), 41 (resolving 0 h), 102 (non-resolving 0 h), 51 (early

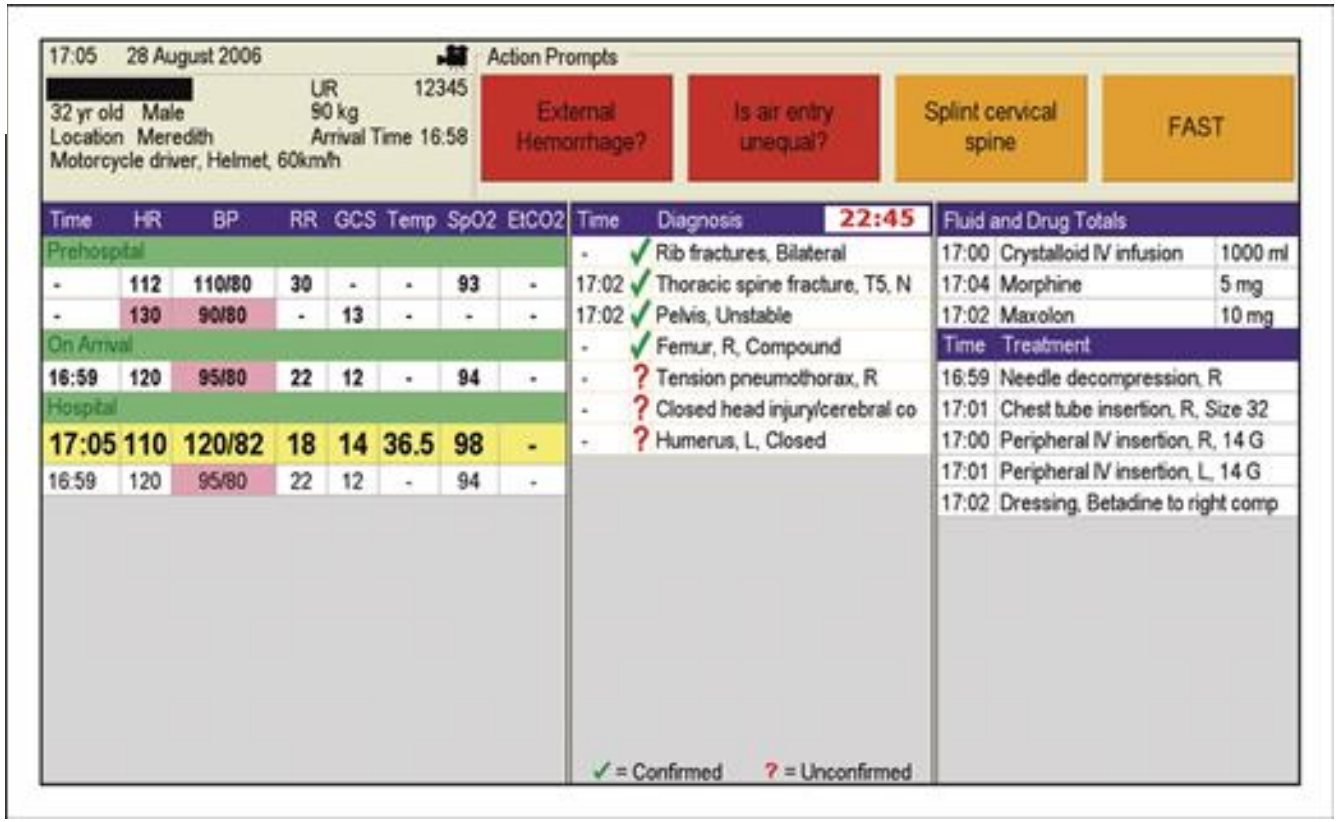
(legend continued on next page)


IA/
DECISION

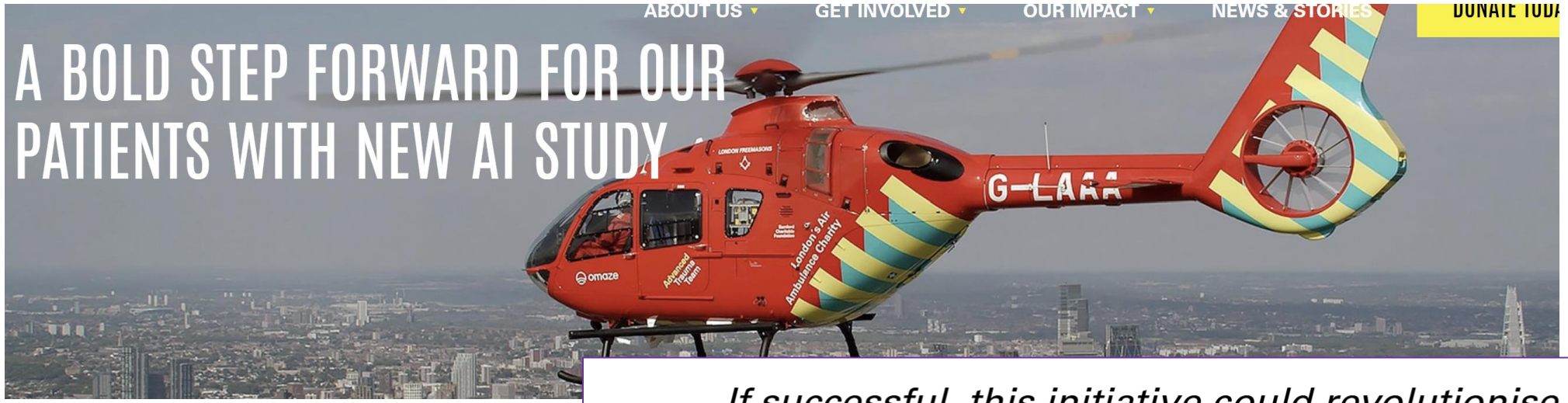
ORIGINAL ARTICLE

Trauma Resuscitation Errors and Computer-Assisted Decision Support

Mark Fitzgerald, MB BS; Peter Cameron, MD BS; Colin Mackenzie, MB, ChB; Nathan Farrow, BN; Pamela Scicluna, BSc; Robert Gocentas, MB BS; Adam Bystrzycki, MB BS; Geraldine Lee, MPhil; Gerard O'Reilly, MB BS; Nick Andrianopoulos, MB BS; Linas Dziukas, MD BS; D. Jamie Cooper, MD BS; Andrew Silvers, MB BS; Alfredo Mori, MB BS; Angela Murray, BN; Susan Smith, CCN; Yan Xiao, PhD; Dion Stub, MB BS; Frank T. McDermott, MD BS; Jeffrey V. Rosenfeld, MD MS



IA DECISION



If successful, this initiative could revolutionise trauma care worldwide and help save thousands of lives.

"This is a pioneering step forward in trauma care,"

ELSEVIER

International Journal of Medical Informatics

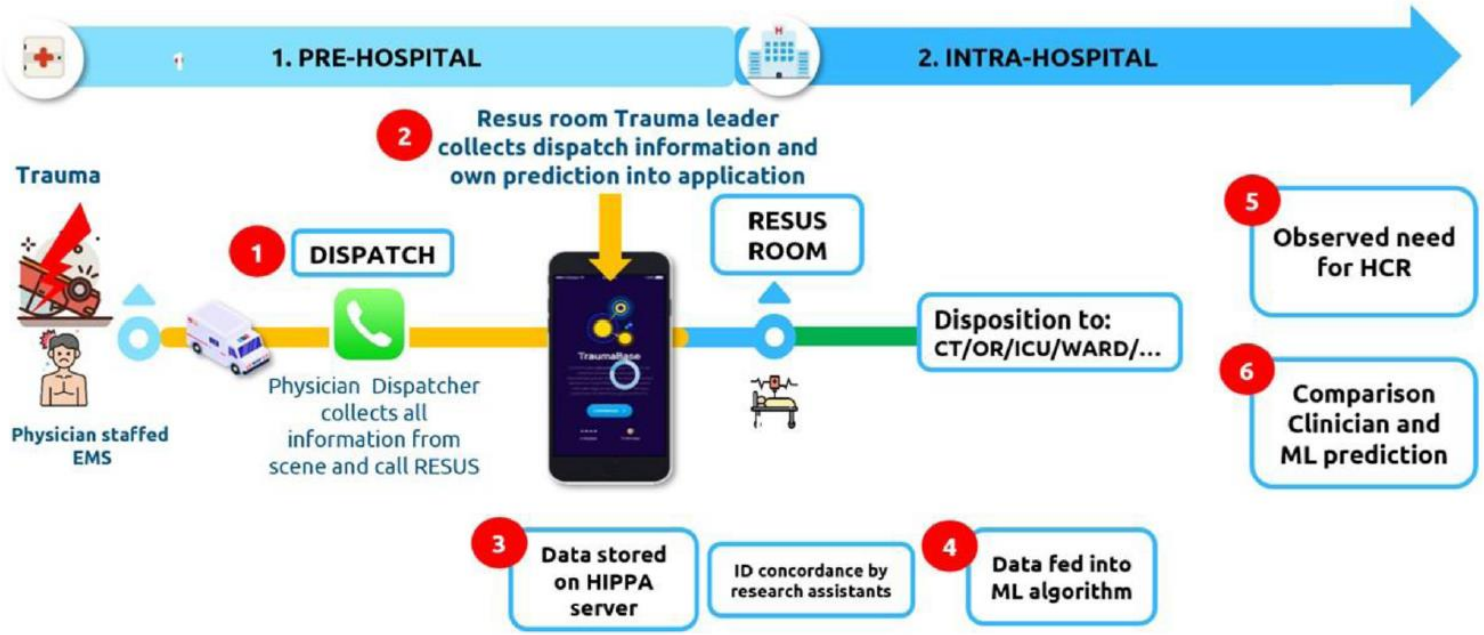
Volume 194, February 2025, 105702

Presenting predictions and performance of probabilistic models for clinical decision support in trauma care

Cansu Alptekin [a] ✉, Jared M. Wohlgemut [b] ✉, Zane B. Perkins [b c] ✉, William Marsh [d] ✉, Nigel R.M. Tai [b c] ✉, Barbaros Yet [a] ✉

Comparison of machine learning and human prediction to identify trauma patients in need of hemorrhage control resuscitation (ShockMatrix study): a prospective observational study

Tobias Gauss,[a,b,*] Arthur James,[c,d] Clelia Colas,[e] Nathalie Delhaye,[f] Mathilde Holleville,[g] Benjamin Bijok,[h] Marie Werner,[i,j] Alain Meyer,[k] Véronique Ramonda,[l] Eric Cesareo,[m] Hugues de Cherisey,[e] Sofiane Medjkoune,[e] Samia Salah,[a] Jean-Pierre Nadal,[n,o] Jean-Denis Moyer,[p] Antoine Vilotitch,[q] Pierre Bouzat,[a,b] and Julie Josse,[r] on behalf of the Traumabase Group



	F4	Sensitivity	Precision	Specificity	Accuracy	AUC ROC	AUC PR	Pos LR	Neg LR
Human clinician [95% CI]	0.64 [0.59–0.74]	0.71 [0.62–0.78]	0.36 [0.30–0.43]	0.81 [0.78–0.84]	0.80 [0.77–0.82]	0.76 [0.71–0.80]	0.29 [0.24–0.35]	3.74 [3.20–4.36]	0.36 [0.29–0.46]
XGBoost model [95% CI]	0.68 [0.60–0.75]	0.71 [0.63–0.80]	0.38 [0.31–0.44]	0.82 [0.80–0.85]	0.81 [0.78–0.83]	0.83 [0.79–0.88]	0.53 [0.44–0.63]	4.01 [3.43–4.7]	0.35 [0.33–0.44]
Hypothetical combined use human clinician and XGBoost [95% CI]	0.76 [0.69–0.82]	0.83 [0.77–0.88]	0.31 [0.30–0.43]	0.73 [0.70–0.75]	0.74 [0.71–0.77]	0.78 [0.74–0.81]	0.29 [0.23–0.34]	3.02 [2.72–3.44]	0.23 [0.17–0.33]

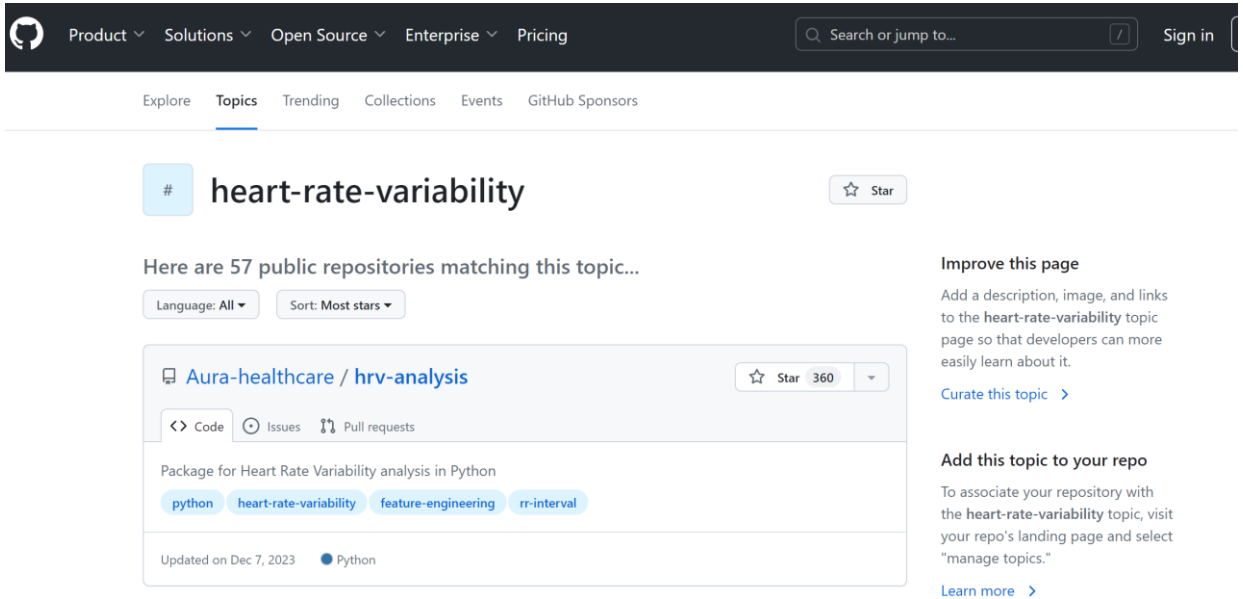
Table 5: Summary of performance metrics human clinician, machine learning (XGBoost) and hypothetical combined use.

IA/ DECISION

SHOCK, Vol. 42, No. 2, pp. 108–114, 2014

UTILITY OF VITAL SIGNS, HEART RATE VARIABILITY AND COMPLEXITY, AND MACHINE LEARNING FOR IDENTIFYING THE NEED FOR LIFESAVING INTERVENTIONS IN TRAUMA PATIENTS

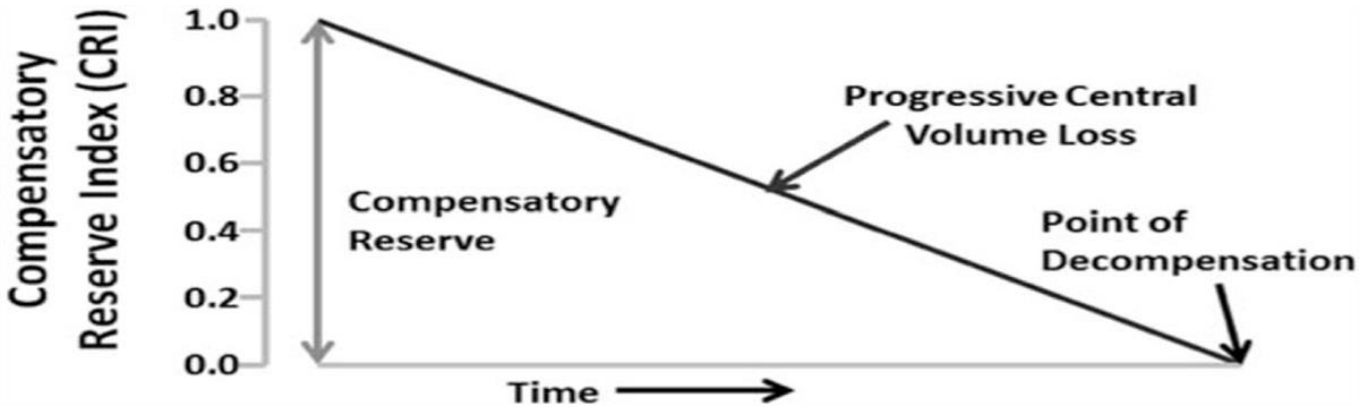
Nehemiah T. Liu,* John B. Holcomb,† Charles E. Wade,† Mark I. Darrah,‡ and Jose Salinas*



DOI : 10.1097/SHK.0000000000000647

TITLE: THE COMPENSATORY RESERVE INDEX FOLLOWING INJURY: RESULTS OF A PROSPECTIVE CLINICAL TRIAL

AUTHORS: CL Stewart[1], J Mulligan[2], GZ Grudic[2], ME Talley[3], GJ Jurkovich[4], SL Moulton[1,2,3]



JAMA Network Open

Original Investigation | Emergency Medicine

A Machine Learning Trauma Triage Model for Critical Care Transport

Aaron C. Weidman, PhD; Salim Malakouti, PhD; David D. Salcido, PhD; Chase Zikmund, MS; Ravi Patel, MS; Leonard S. Weiss, MD; Michael R. Pinsky, MD; Gilles Clermont, MD; Jonathan Elmer, MD; Ronald K. Poropatich, MD; Joshua B. Brown, MD; Francis X. Guyette, MD

Key Points

Question Can machine learning analysis of patient physiological signals predict the need for prehospital lifesaving intervention?

Findings In this cohort study of 2809 patients with trauma and critical illness, continuous physiologic waveform signals and derived vital sign patterns were fed into an ensemble machine learning classifier to predict administration of prehospital lifesaving interventions within 2-minute treatment epochs (eg, airway intervention, blood transfusion). The model achieved good performance, which was maintained using physiological features captured up to 15 minutes prior to intervention.

Meaning These findings suggest that modeling approaches have the potential to streamline and augment prehospital trauma triage.

Table 2. Machine Learning Results Predicting LSI and Each Specific Category

		Metric (95% CI)			
LSI administered[a]	Per-epoch rate	AUROC	Sensitivity	Positive predictive value	Positive likelihood ratio
All	0.060	0.810 (0.782-0.842)	0.268 (0.193-0.357)	0.301 (0.228-0.356)	6.793 (4.887-8.795)
Airway intervention	0.0352	0.910 (0.888-0.932)	0.277 (0.178-0.378)	0.259 (0.193-0.335)	9.726 (6.533-13.891)
Bleeding control	0.0133	0.580 (0.486-0.658)	0.018 (0.000-0.057)	0.019 (0.000-0.066)	1.475 (0.000-5.481)
Blood transfusion	0.0066	0.784 (0.688-0.872)	0.040 (0.000-0.140)	0.042 (0.000-0.188)	7.056 (0.000-29.719)
Vasopressor medication	0.0046	0.816 (0.652-0.916)	0.064 (0.000-0.238)	0.057 (0.000-0.212)	14.472 (0.000-62.243)
Thoracic intervention	0.0027	0.675 (0.478-0.828)	0.002 (0.000-0.002)	0.002 (0.000-0.001)	0.463 (0.000-1.641)
Cardiovascular intervention	0.0014	0.650 (0.222-0.992)	0.031 (0.000-0.500)	0.015 (0.000-0.173)	16.445 (0.000-177.590)

Abbreviations: AUROC, area under the receiver operating characteristics curve; LSI, lifesaving intervention.

[a] Includes 15 088 two-minute epochs. All metrics are calculated at the per-epoch level. The 95% CIs are calculated via empirical bootstrapping.

NEJM AI

DOI: 10.1056/AIcs2401170

CASE STUDY

A Case Study of AI-Enabled Software as a Medical Device Cleared by the FDA for Assessing Hemorrhage Risk Index (APPRAISE-HRI) after Trauma

Andrew Frock, B.S.,[1,2] Jeffrey T. Robbins, B.S.,[1,2] Francisco G. Vital-Lopez, Ph.D.,[1,2] Valmik Desai, M.S.,[1,2] Gheorghe Doros, Ph.D., M.B.A.,[3] Barry E. Sands, B.S.B.M.E., M.B.A.,[3] Arunkumar Prabhakaran, Pharm.D., M.S.-R.A.,[3] Christopher Nemeth, Ph.D., C.H.F.P.,[4] Gregory T. Rule, M.S.E., P.E.,[4] Jason L. Sperry, M.D., M.P.H.,[5] Francis X. Guyette, M.D., M.P.H.,[6] Stephen R. Wisniewski, Ph.D.,[7] Ernest E. Moore, M.D.,[8] Martin Schreiber, M.D.,[9] Bellal Joseph, M.D.,[10] Chad T. Wilson, M.D.,[11] Bryan Cotton, M.D.,[12] Daniel Ostermayer, M.D.,[13] Brian G. Harbrecht, M.D.,[14] Mayur B. Patel, M.D., M.P.H.,[15] Suzanne Tamang, Ph.D.,[16,17] Sanjay Malunjkar, B.E.,[17] David A. Spain, M.D.,[18] Andrew T. Reisner, M.D.,[19] Jonathan D. Stallings, Ph.D.,[20] and Jaques Reifman, Ph.D.[1]

Received: December 2, 2024; Revised: July 11, 2025; Accepted: August 25, 2025; Published: October 16, 2025

3 cohorts

Outputs

ICD-10/AIS Transfusi

Output 10%

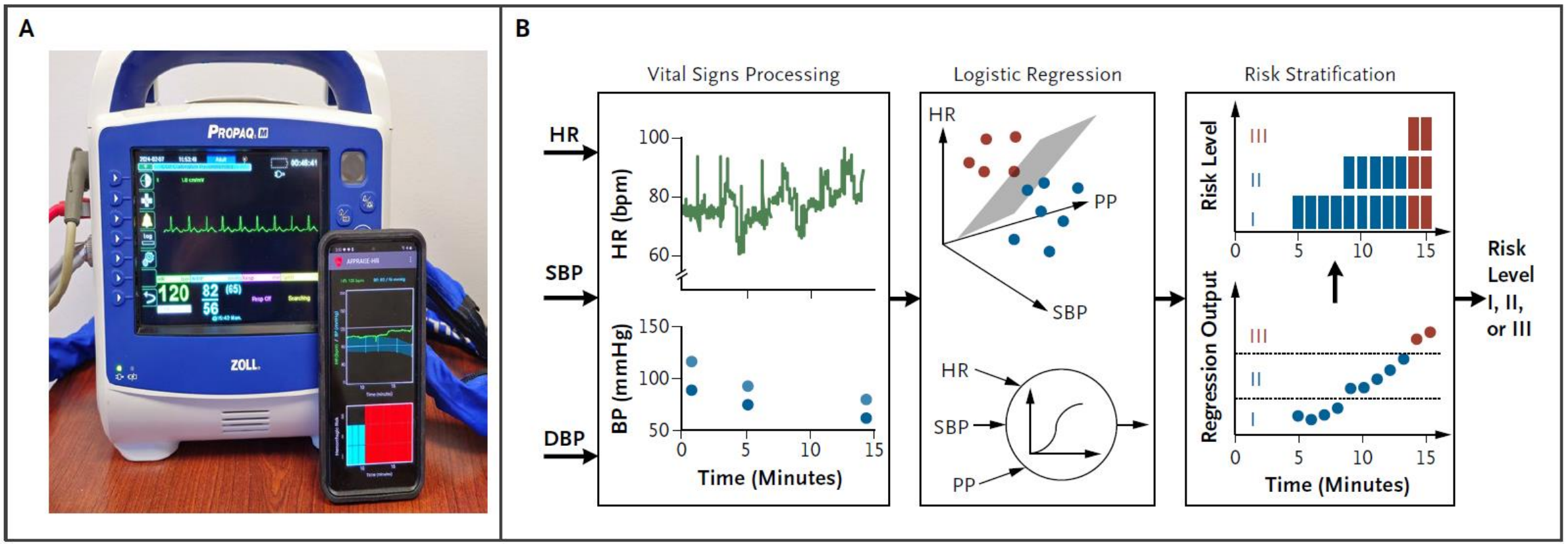


Figure 1. APPRAISE-HRI Software as a Medical Device.

Table 2. Primary Outcome Using the Device's First Output for Each Patient.*

HRI Level	Hemorrhagic, N	Control, N	Total, N	Likelihood Ratio (95% CI)†	Posttest Probability % (95% CI)
I	25	1347	1372	0.18 (0.12 to 0.26)	1.8 (1.2 to 2.5)
II	257	3631	3888	0.70 (0.63 to 0.76)	6.6 (6.1 to 7.2)
III	261	374	635	6.88 (6.04 to 7.84)	41.0 (38.0 to 44.3)
Total	543	5352	5895	–	–

No prospective validation

No workflow integration

No provider comparison

Not superior to SI > 1,4

Pinsky *et al.*
Intensive Care Medicine Experimental (2024) 12:44
https://doi.org/10.1186/s40635-024-00628-5

Intensive Care Medicine Experimental

RESEARCH ARTICLES Open Access

Autonomous precision resuscitation during ground and air transport of an animal hemorrhagic shock model

Michael R. Pinsky[1,2*], Hernando Gomez[1], Francis X. Guyette[3], Leonard Weiss[3], Artur Dubrawski[4], Jim Leonard[4], Robert MacLachlan[4], Lisa Gordon[1], Theodore Lagattuta[1], David Salcido[3] and Ronald Poropatich[1,2,5]

Uncontrolled haemorrhage model PIG

LIDCO SWAN

MAP HR PPV SVV EadvN

MAP<60m mHg HR > 110

250ml fluid Blood Ca NAD

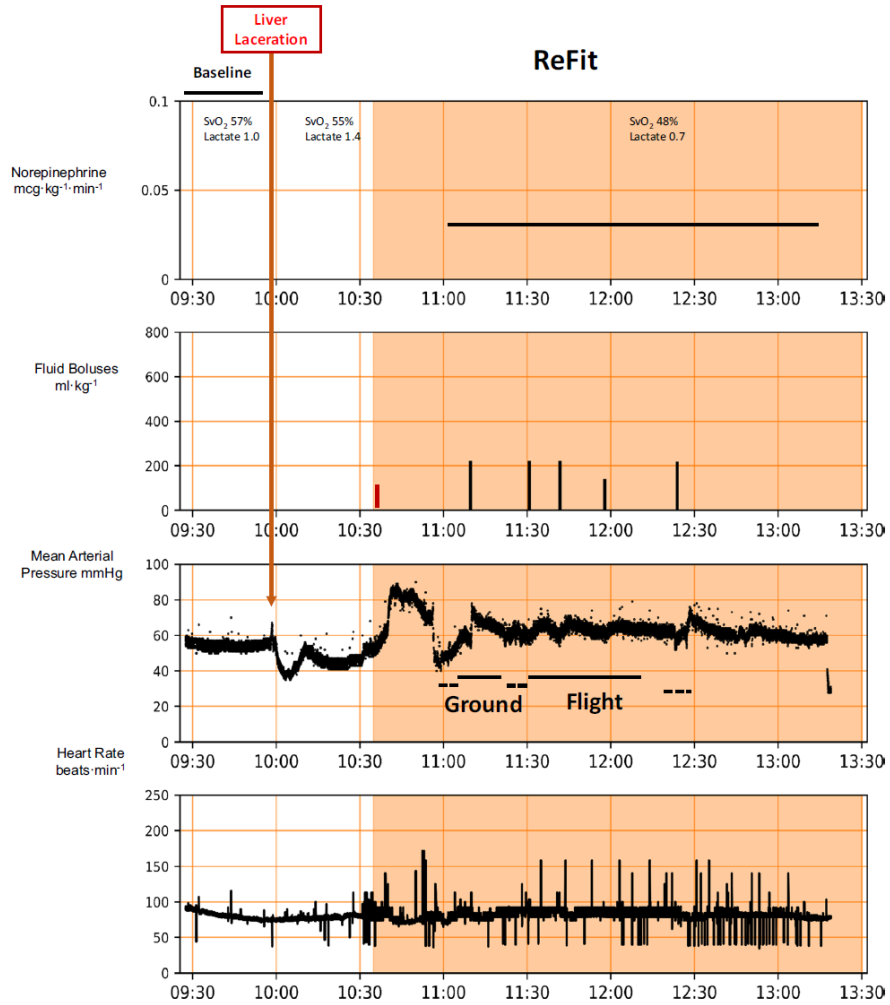


Fig. 5 Similar physiologic trend displays as Fig. 4 for the fourth animal to be transported first by ground to a remote airport covering 9.1 miles in 30 min then flown back to the hospital by rotary wing transport for 35 min covering 62.3 miles

Table 2 Hemodynamic data at across the protocol

	MAP mmHg	HR beats · min^{-1}	SaO_2%	SvO_2%	Hbg gm/dl	CO l·min^{-1}
ReFit Lab only *N* = 8						
Baseline	68.8 ± 3.7	82.2 ± 17.6	100 ± 0	57 ± 6	10.6 ± 1.2	2.75 ± 1.31
Pre-resuscitation	48.6 ± 4.9	102.4 ± 21.6	100 ± 0	43 ± 10	9.1 ± 1.6	1.62 ± 0.93
At Initial stabilization	75.5 ± 9.2	77.0 ± 11.1	100 ± 0	64 ± 5	8.3 ± 1.6	2.75 ± 0.58
2 h post-initial stabilization	68.1 ± 6.0	74.9 ± 10.2	100 ± 0	59 ± 11		2.83 ± 139
ReFit 2 Lab and transport *N* = 4						
Baseline	62.4 ± 3.7	87..8 ± 3.6	97 ± 2		8.6 ± 1.5	
Pre-resuscitation	48.9 ± 2.0	86.6 ± 3.4	97 ± 2		8.7 ± 1.3	
At initial stabilization	70.4 ± 12.3	80.8 ± 3.7	96 ± 2		9.3 ± 0.9	
2 h post-initial stabilization	60.6 ± 5.4	78.4 ± 2.8	94 ± 2			

Mean ± standard deviation of mean arterial pressure (MAP), heart rate (HR), mixed venous O_2 saturation (SvO_2) and cardiac output (CO) for the three experimental groups over the same time points in the protocol. Note SvO_2 and CO were not continuously measures in the 4 animals study for transport

frontiers in Medicine

ORIGINAL RESEARCH
published: 17 March 2022
doi: 10.3389/fmed.2022.851690

Deep Learning-Based Pain Classifier Based on the Facial Expression in Critically Ill Patients

Chieh-Liang Wu[1,2,3,4†], Shu-Fang Liu[5†], Tian-Li Yu[6], Sou-Jen Shih[5], Chih-Hung Chang[6], Shih-Fang Yang Mao[7], Yueh-Se Li[7], Hui-Jiun Chen[5], Chia-Chen Chen[7] and Wen-Cheng Chao[1,4,8,9*]*

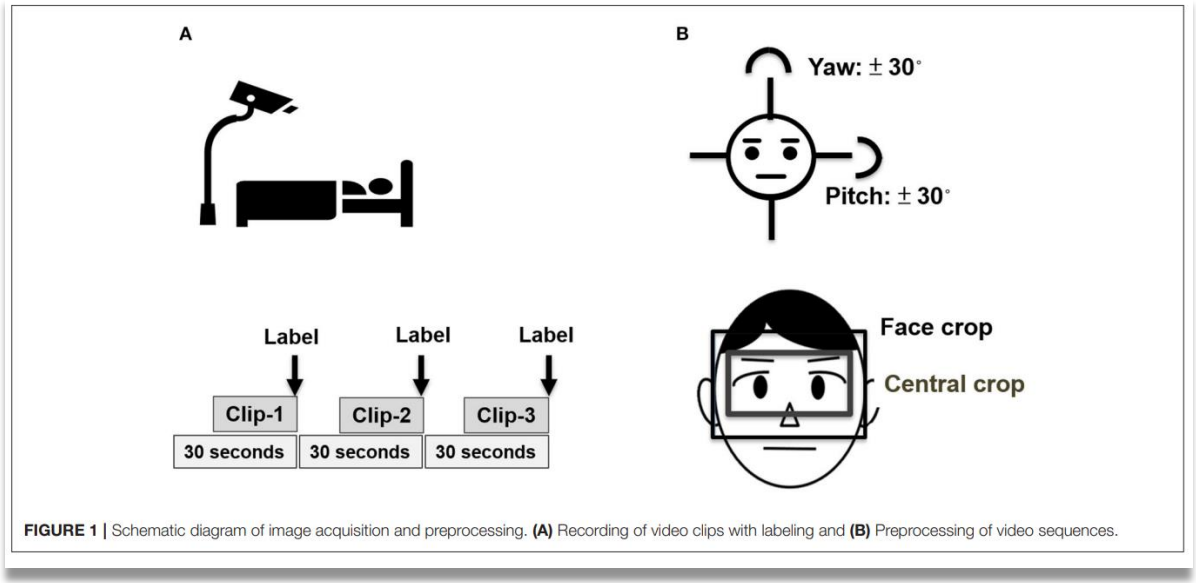


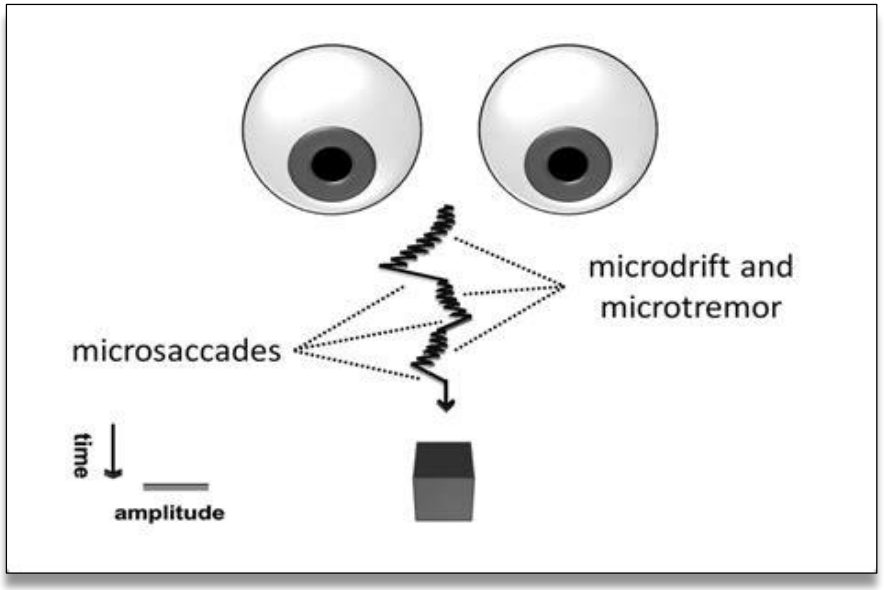
FIGURE 1 | Schematic diagram of image acquisition and preprocessing. **(A)** Recording of video clips with labeling and **(B)** Preprocessing of video sequences.

Experimental Brain Research (2023) 241:2191–2203
https://doi.org/10.1007/s00221-023-06691-w

REVIEW

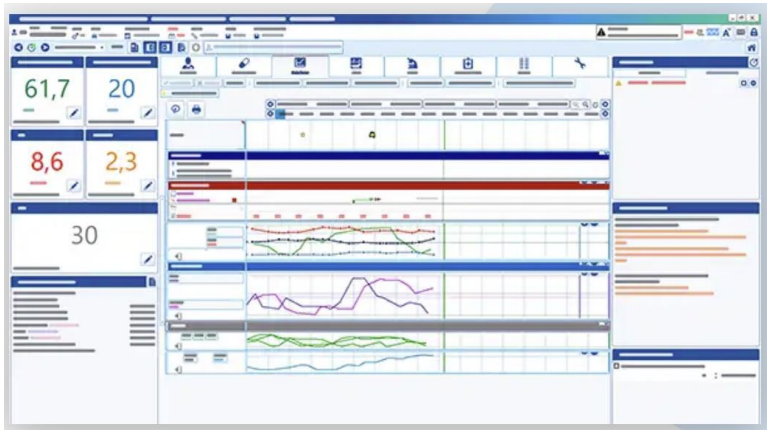
Ocular microtremor: a structured review

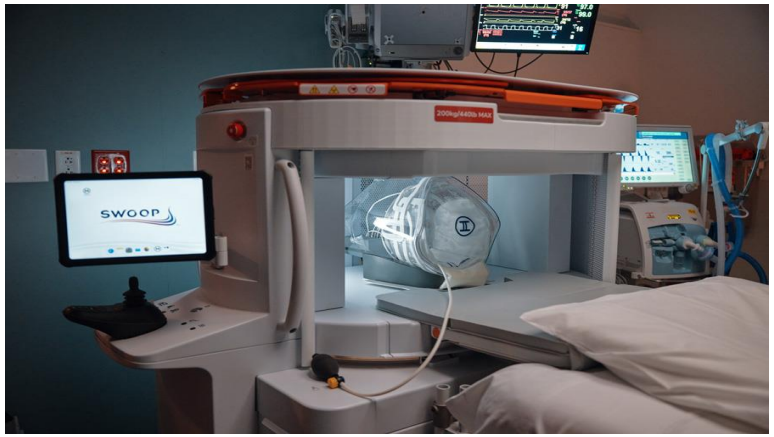
Lisa Graham[1,2] · Julia Das[1,3] · Rodrigo Vitorio[1] · Claire McDonald[2] · Richard Walker[3] · Alan Godfrey[4] · Rosie Morris[1,3] · Samuel Stuart[1,3,5]

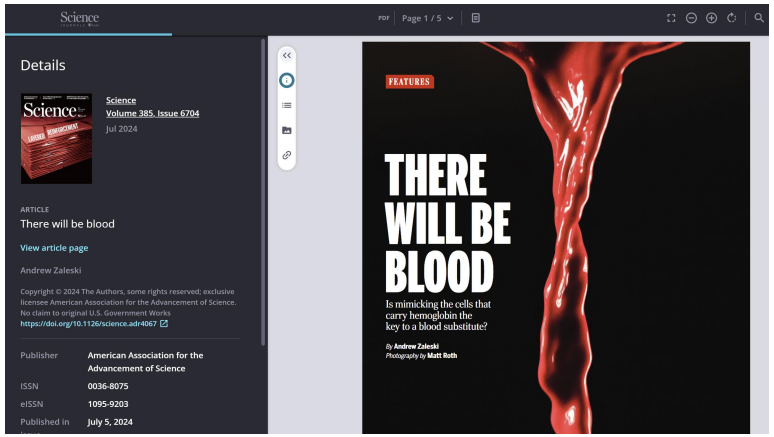


CONCLUSION

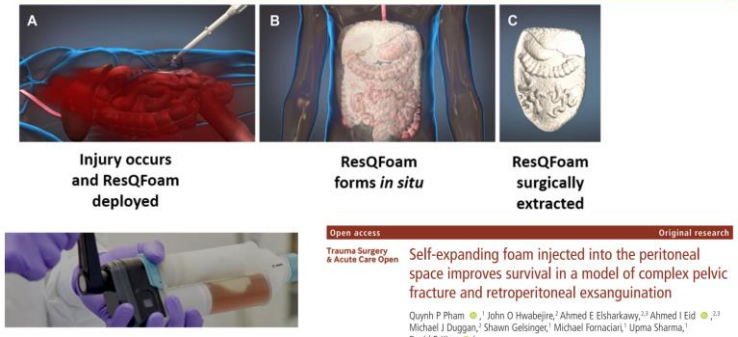
CONCLUSION







TECH



Open access Original research

Trauma Surgery & Acute Care Open

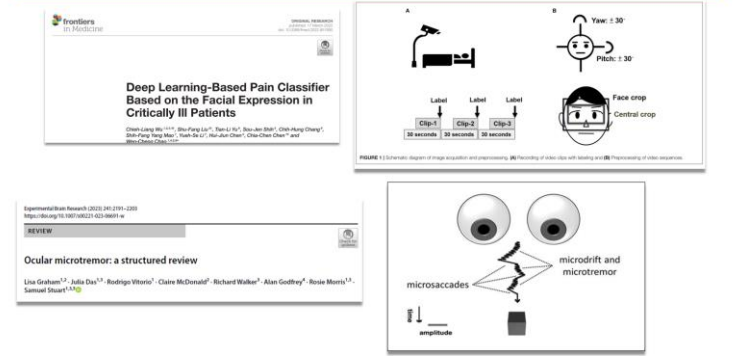
Self-expanding foam injected into the peritoneal space improves survival in a model of complex pelvic fracture and retroperitoneal exsanguination

Quynh P Pham, John O Hwabejire, Ahmed E Elsharkawy, Ahmed I Eid, Michael J Duggan, Shawn Gelsinger, Michael Fornaciari, Upma Sharma, David R King

Comparison of machine learning and human prediction to identify trauma patients in need of hemorrhage control resuscitation (ShockMatrix study): a prospective observational study

Tobias Gauss, Arthur James, Clelia Colas, Nathalie Delhaye, Mathilde Holleville, Benjamin Bijok, Marie Werner, Alain Meyer, Véronique Ramonda, Eric Cesareo, Hugues de Cherisey, Sofiane Medjkoune, Samia Salah, Jean-Pierre Nadal, Jean-Denis Moyer, Antoine Vilotitch, Pierre Bouzat, and Julie Josse, on behalf of the Traumabase Group

IA/ DECISION



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MERCI POUR VOTRE ATTENTION