Advanced Technologies for Preventing and Diagnosing Kidney Disease and Improving Guideline-Informed Care: Peering Through the Crystal Ball

Jay L. Koyner MD
University of Chicago

Disclosures – for the last 24 months

- Research Funding from NIH, Astute Medical-Biomerieux, Bioporto, Sphingotec
- Prior Consulting Fees from Alexion, Astute-Biomerieux, Baxter-Vantive , Bioporto, Fresenius SeaStar, Novartis, Guard Therapeutics
- Honoraria – ASN, ISICEM
- Royalties – Wolters Kluwer
- Scientific Advisor/Membership – American Journal of Nephrology, CJASN and Kidney360 editorial board. Scientific Ad Board for KF of Illinois; Scientific Ad Board for NKF
- **I like to #nephBBQ**
- **I am a Nephrologist who does AKI research around AKI risk stratification, care and outcomes with and without Artificial Intelligence**

Outline / Objectives for the talk (as given to me)

- Role and adoption of AI, machine learning, etc. in nephrology (cite examples from use for AKI prediction, prognostication)

- Other advanced technologies (e.g., wearables, home monitoring, implantables, generative AI, agentic AI, etc.)

- Barriers and facilitators to the development and implementation of new technology

If we ask generative AI what it thinks about AI in Nephrology

Current Applications:

Early Detection and Prediction
- AKI, CKD, Transplant (matching and graft function)

ESKD Management
- Dose , Dry Weight, Low BP

Access care, Infections

Real Time Monitoring

Drug Dosing

Decision Support

Imaging

Challenges
- Data Quality
- Work-Flow Integration
- Ethical Concerns

Summary Table

Dimension	Status (2025)	Readiness
Research evidence	Strong	✅
Clinical validation	Moderate	⚠️
Regulatory approval	Limited	⚠️
Integration into care	Low	❌
Clinician acceptance	Growing	⚠️

→ **Verdict:** *Nephrology is on the verge of readiness, but not yet in everyday AI-driven practice.*

Liu *et al.*
BMC Medical Informatics and Decision Making (2023) 23:157
https://doi.org/10.1186/s12911-023-02254-9

BMC Medical Informatics and Decision Making

RESEARCH ARTICLE Open Access

Discrepancy between perceptions and acceptance of clinical decision support Systems: implementation of artificial intelligence for vancomycin dosing

Xinyan Liu[1,2], Erin F. Barreto[3], Yue Dong[4], Chang Liu[1,5], Xiaolan Gao[1,6], Mohammad Samie Tootooni[7], Xuan Song[8*] and Kianoush B. Kashani[1,9*]

- 60-70% of Pharmacist think CDSS is useful
- But lots of discrepancy between AI and humans on the best dose - 80% of the time

Open access Protocol

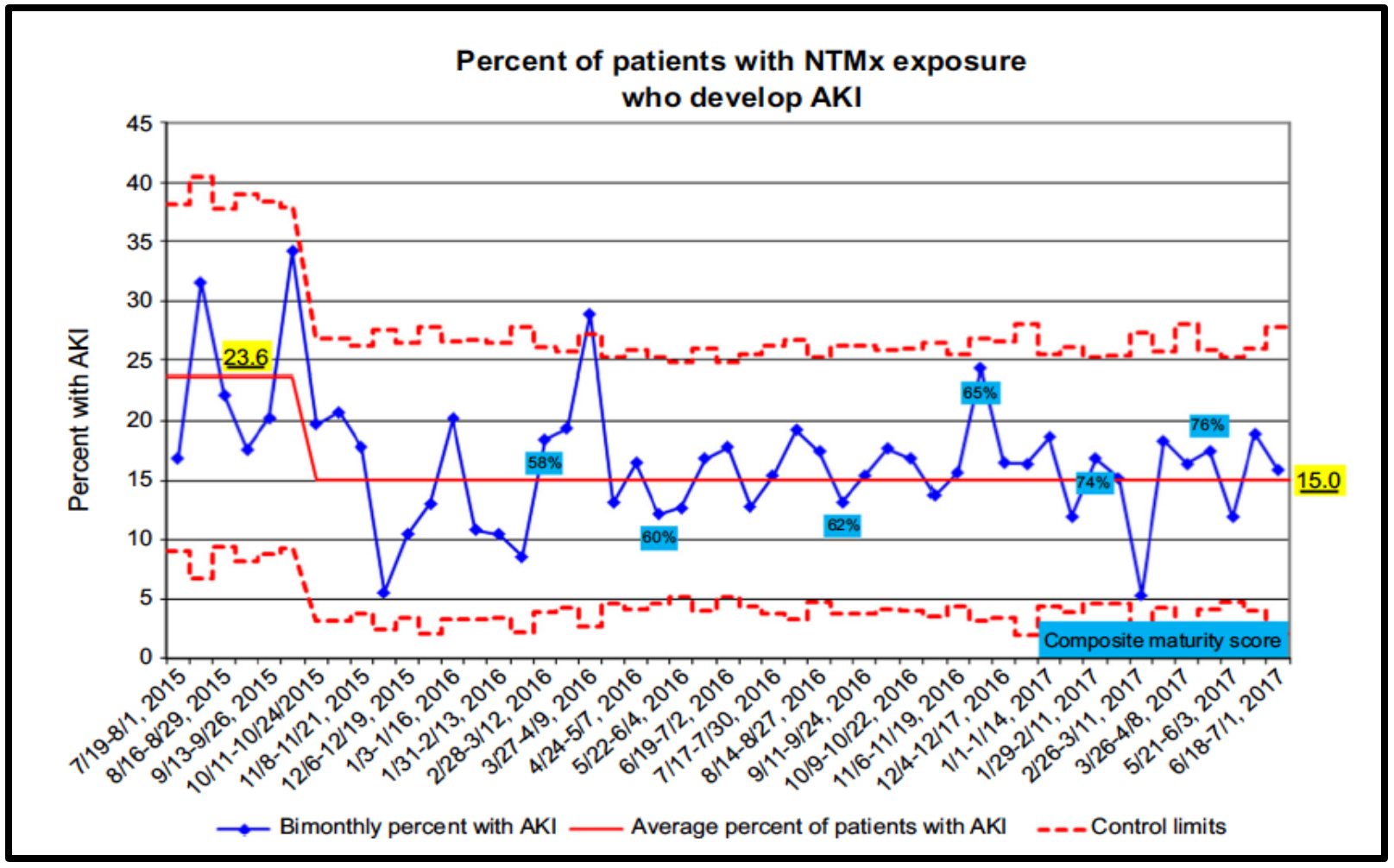
BMJ Open

Employing artificial intelligence for optimising antibiotic dosages in sepsis on intensive care unit: a study protocol for a prospective observational study (KI.SEP)

Britta Marko,[1] Lars Palmowski,[1] Hartmuth Nowak,[1,2] Andrea Witowski,[1] Björn Koos,[1] Katharina Rump,[1] Lars Bergmann,[1] Julia Bandow,[3,4] Martin Eisenacher,[5,6] Patrick Günther,[7] Michael Adamzik,[1] Barbara Sitek,[1,5] Tim Rahmel[1]

Trials are coming…..

Multi-Center Validation of NINJA: Goldstein et al : Kid Int 2020



- 9 Center validation
- Non-critically ill pediatric patients

Recs:

- SCr Measurement in high risk pts
- Recs around non-nephrotoxic options

A sustained 23.8% reduction in Nephrotoxic AKI

JAMA

QUESTION Do diagnostic and therapeutic recommendations from a kidney action team through the electronic health record (EHR) prevent the primary outcome of worsening kidney injury, dialysis, or mortality among hospitalized patients with acute kidney injury (AKI)?

CONCLUSION Recommendations from a kidney action team did not significantly reduce the composite outcome of worsening AKI stage, dialysis, or mortality.

POPULATION

2129 Men
1874 Women

Adult hospitalized patients with AKI

Mean age: 71 years

LOCATIONS

7
Hospitals in the US

INTERVENTION

4003 Patients randomized

1999

Received recommendation note
Kidney action team sent personalized recommendations via EHR

2004

Did not receive recommendation note
No recommendation was sent via EHR

PRIMARY OUTCOME

Composite outcome consisting of AKI progression to a higher stage of AKI, dialysis, or mortality occurring while hospitalized and within 14 days of randomization

FINDINGS

Composite outcome

Received recommendation note	Did not receive recommendation note
19.8% (395 of 1999 patients)	18.4% (369 of 2004 patients)

Recommendations from a kidney action team did not significantly reduce worsening AKI stage, dialysis, or mortality:

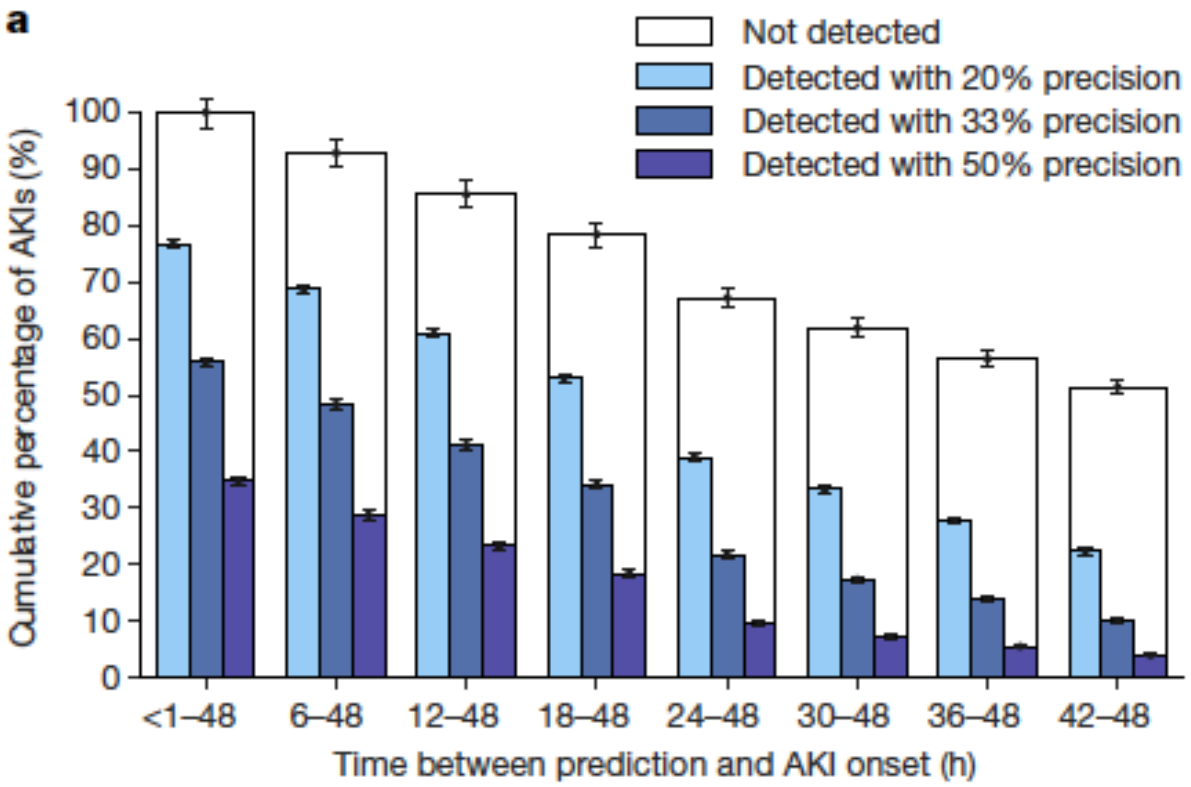
Difference, 1.4% (95% CI, −1.1% to 3.8%); $P = .28$

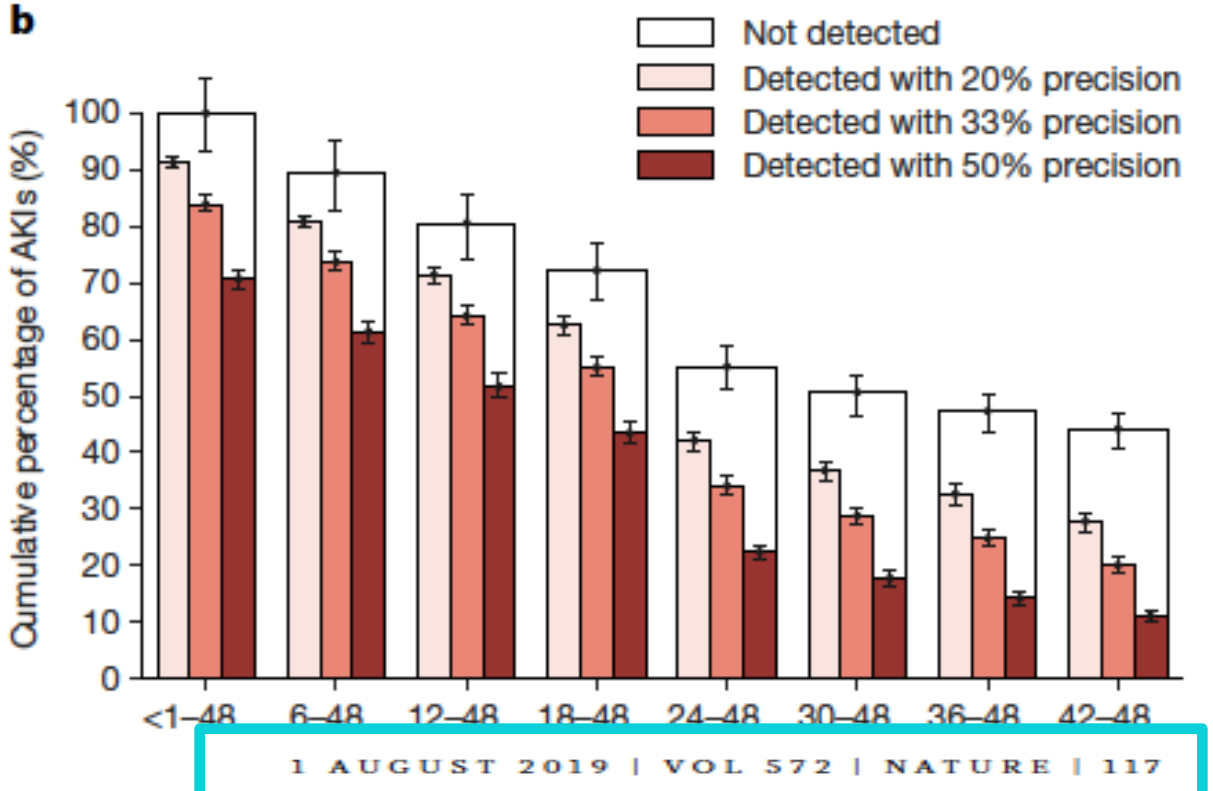
Aklilu AM, Menez S, Baker ML, et al; KAT-AKI Team. Early individualized recommendations for hospitalized patients with acute kidney injury: a randomized clinical trial. *JAMA*. Published online October 25, 2024. doi:10.1001/jama.2024.22718

Extended Data Table 1 | Model performance for predicting AKI within the full range of possible prediction windows from 6 to 72 h

a

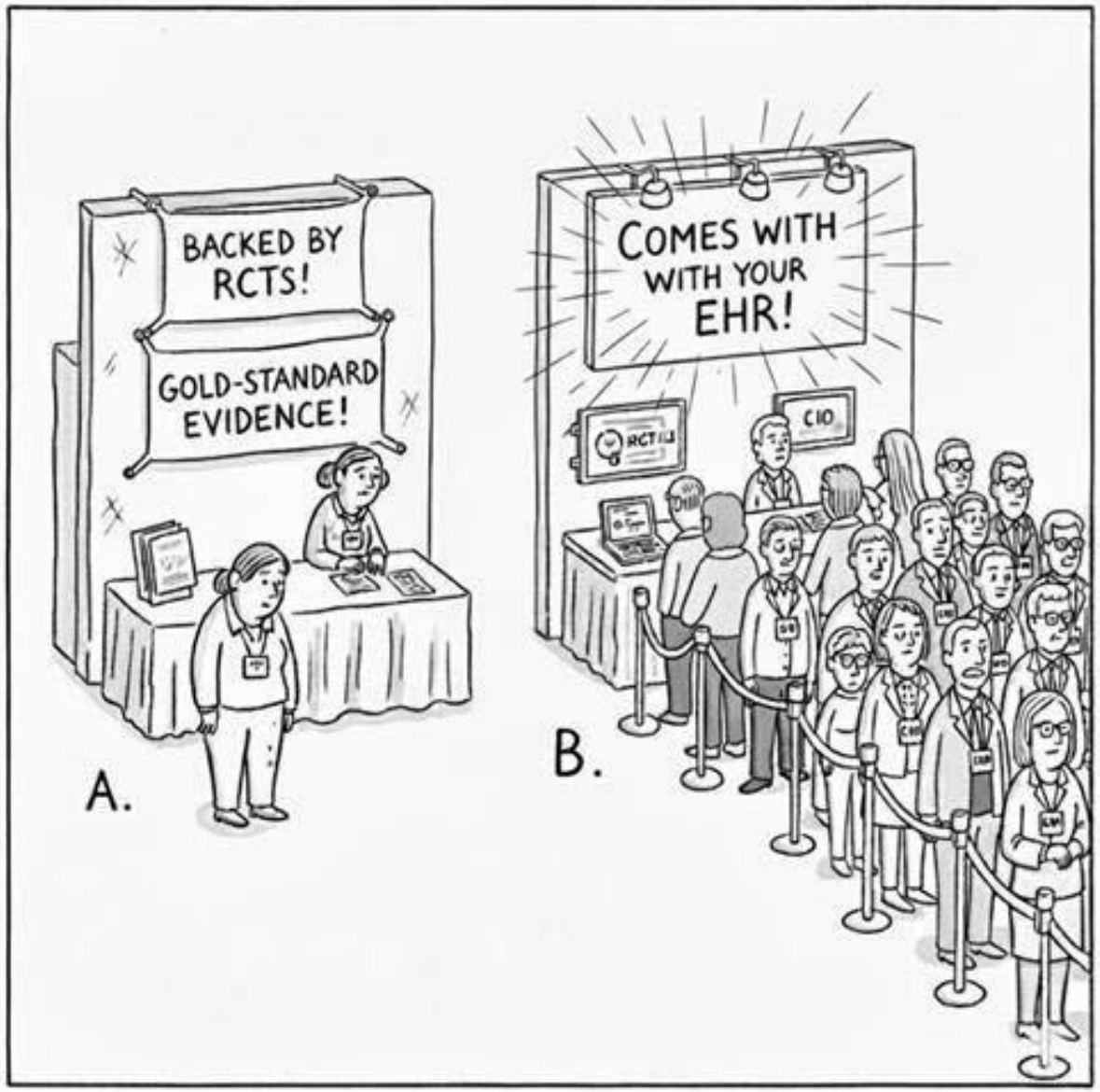
Time windows	ROC AUC [95% CI]		
	Any AKI	AKI stages 2 and 3	AKI stage 3
24h	93.4% [93.3, 93.6]	97.1% [96.9, 97.3]	98.8% [98.7, 98.9]
48h	92.1% [91.9, 92.3]	95.7% [95.5, 96.0]	98.0% [97.8, 98.2]
72h	91.4% [91.1, 91.6]	94.7% [94.4, 95.0]	97.3% [97.2, 97.6]





9

Room/Bed	Admission Diagnosis	AKI Candidate	Creatinine	Treatment Team	AKI Score	AKI Candida 2.0	Admission Date
8079/A	Right sided weakness Cerebrovascular accident (CVA), unspecified...	0.02694	! 3 mg...	Paul E Kukulski, M.D. - Admitting (Tel. 773-702-9500)...	0.02694	0.1274	6/12/24
4074A/A	Mitral valve disorder Severe mitral stenosis by prior echocardiogram	0.03223	! 2.4 ...	Christopher T Salerno, M.D. - Admitting (Tel. 773-702-2500)...	0.03223	0.1228	6/14/24
8003/A	AKI (acute kidney injury) (CMS/HCC)	0.00171	! 14.6 ...	John W Moroney, M.D. - Admitting (Tel. 773-702-6123)...	0.00171	0.1175	6/18/24
8070/A	Subdural hematoma (CMS/HCC)	N/A	! 0.4 ...	Ali Mansour, M.D. - Admitting (Tel. 773-702-6222) (Pgr....	N/A	0.1170	5/12/24
8051/A	Altered mental status, unspecified altered mental status type...	0.07759	! 4.5 ...	David A Harter, M.D. - Admitting (Tel. 773-702-9500)...	0.07759	0.1134	6/15/24
8034/A	Cardiac arrest (CMS/HCC) Fracture Endotracheally intubated...	0.00976	! 1.7 ...	Adriana S Olson, M.D. - Admitting (Tel. 773-702-9500)...	0.00976	0.1118	6/17/24
4046/A	Aortic valve disorder Moderate aortic insufficiency	0.07909	! 3.3 ...	Takeyoshi Ota, M.D. - Admitting (Tel. 773-702-2500) (Pgr....	0.07909	0.1090	6/17/24
8037/A	Ischemic stroke (CMS/HCC)	0.10255	1.2 mg/dL	Emily L Jameyfield, M.D. - Admitting (Tel. 203-430-4000)...	0.10255	0.1090	5/29/24
8039/A	Reported gun shot wound Gunshot wound of neck, initial encounter	0.01165	0.6 mg/dL	Christos Lazaridis, M.D. - Admitting (Tel. 773-702-6222)...	0.01165	0.1067	6/10/24
8024/A	Hand ulceration with necrosis of bone (CMS/HCC)...	0.00211	! 11.9 ...	Jeffrey G Stepan, M.D. - Admitting (Tel. 773-834-3531)...	0.00211	0.0976	6/18/24
4048/A	HFrEF (heart failure with reduced ejection fraction) (CMS/HCC)	0.00074	! 2.9 ...	Gene H Kim, M.D. - Admitting (Tel. 773-702-4720) (Pgr...	0.00074	0.0974	5/31/24



"What was the point of doing all those RCTs if the decision makers don't actually care?"

ORIGINAL ARTICLE

External Validation of a Commercial Acute Kidney Injury Predictive Model

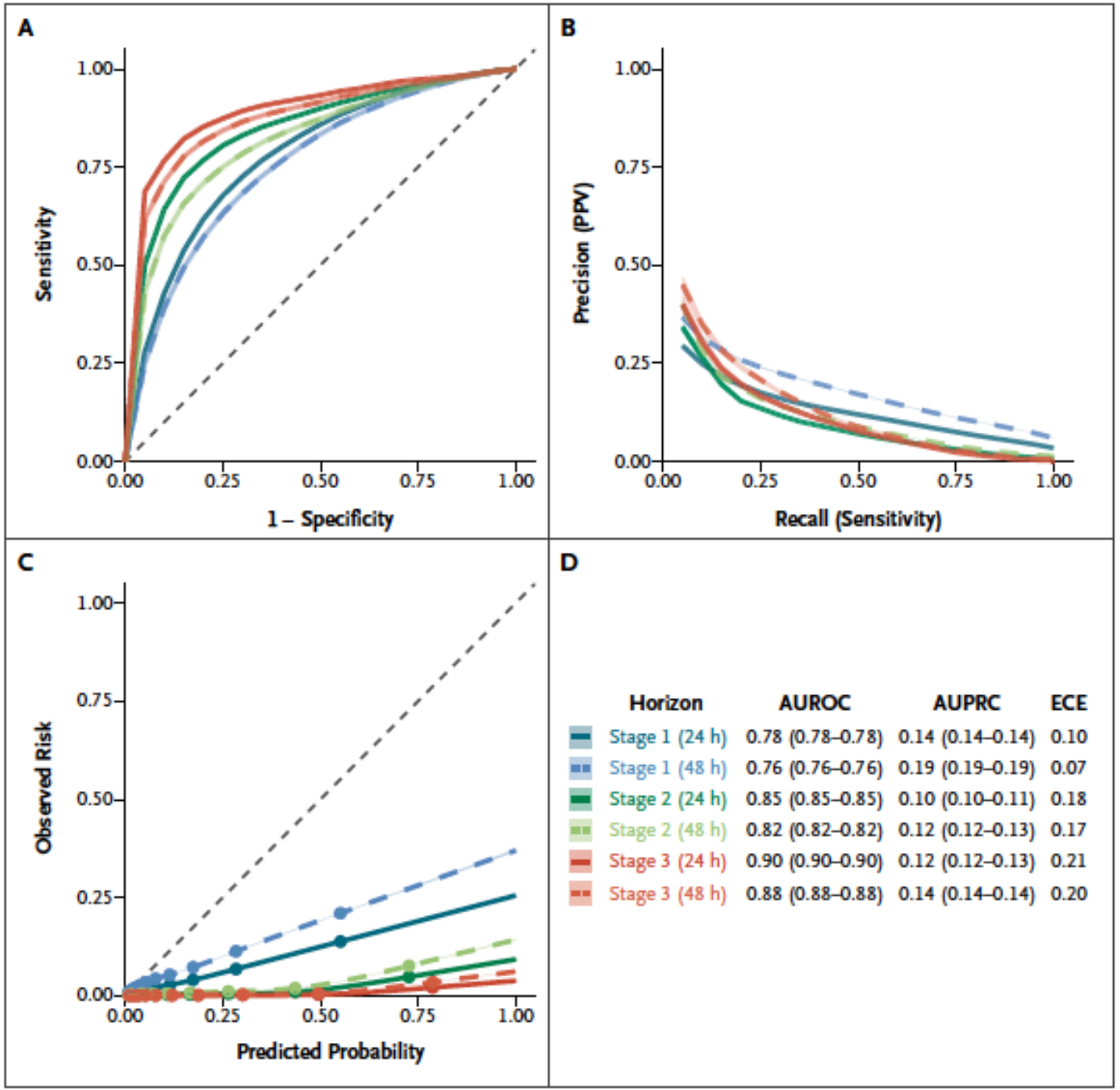
Sayon Dutta, M.D., M.P.H.,[1,2] Dustin S. McEvoy, B.S.,[2] Lisette N. Dunham, M.P.S., M.S.P.H.,[2] Ronelle Stevens, Pharm.D.,[2] David Rubins, M.D.,[2,3] Gearoid M. McMahon, M.B., B.Ch., M.D.,[3] and Lipika Samal, M.D., M.P.H.[3]

Received: August 25, 2023; Revised: October 27, 2023; Accepted: November 21, 2023; Published: February 7, 2024

- Over 39,000 Admissions
- 24.5% developed KDIGO Stage 1
- AUROC for Stage 1 0.77(0.76 to 0.78)
- Within 48 hours
  - AUROC 0.76 (0.76 to 0.76)
  - AUPRC 0.19 (0.19 to 0.19)
- Value of 50 provided
  - PPV of 88
  - Sensitivity of 50%
  - 21 hours advanced notice….

Precision-recall curve (AUPRC)

- Precision = TP / (TP +FP)
- Recall = TP / (TP + FN)



JAMA Network™

From: **Factors Associated With Variability in the Performance of a Proprietary Sepsis Prediction Model Across 9 Networked Hospitals in the US**

JAMA Intern Med. Published online April 03, 2023. doi:10.1001/jamainternmed.2022.7182

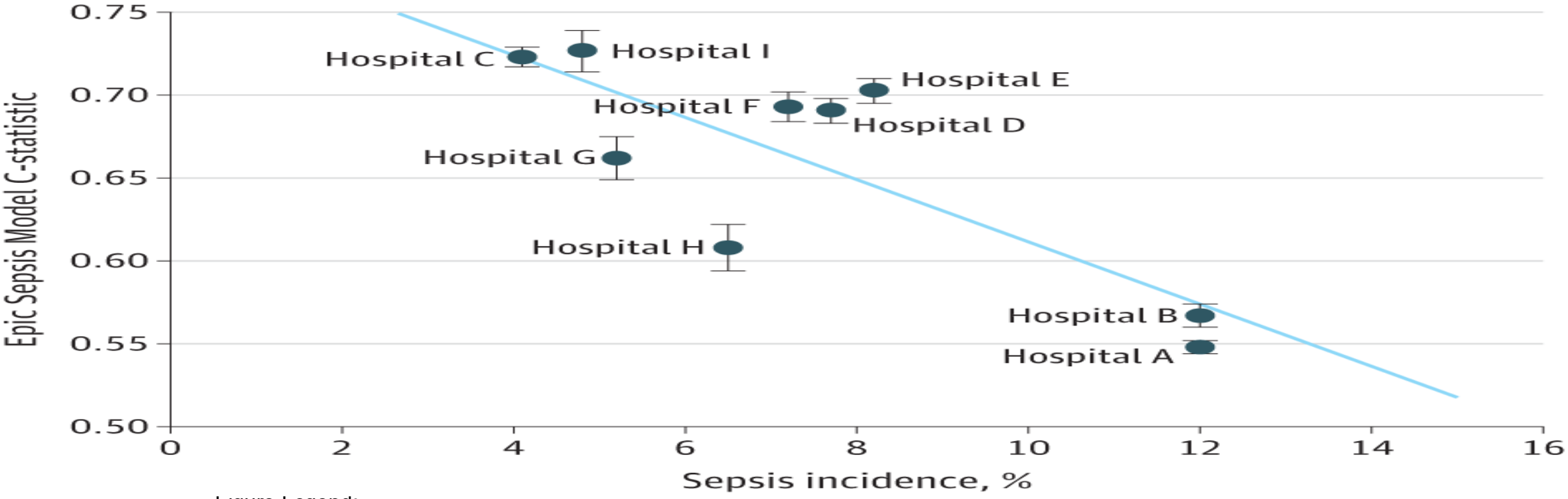
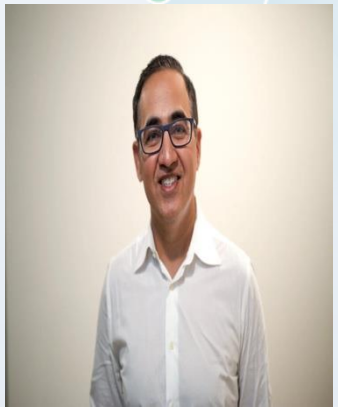


Figure Legend:

Association Between Hospital-Level Sepsis Incidence and Epic Sepsis Model C-Statistic Across 9 US Hospitals in a NetworkEach hospital is represented by a blue point (A through I), with 95% CIs represented by vertical bars. The diagonal line represents the line of best fit among hospitals A through I.

On to CKD (Briefly….)



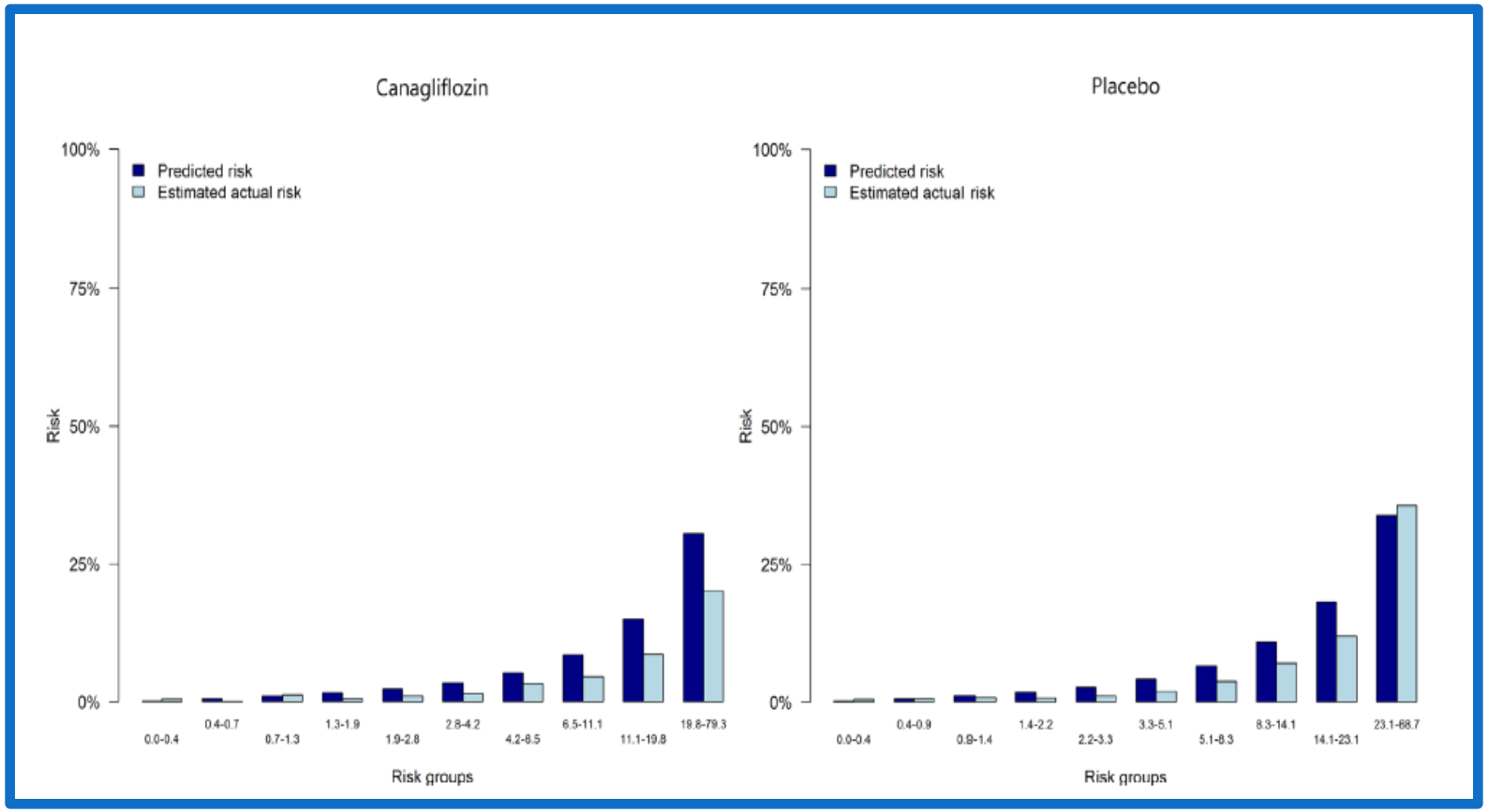
Received: 5 April 2024 | Revised: 26 April 2024 | Accepted: 4 May 2024
DOI: 10.1111/dom.15678

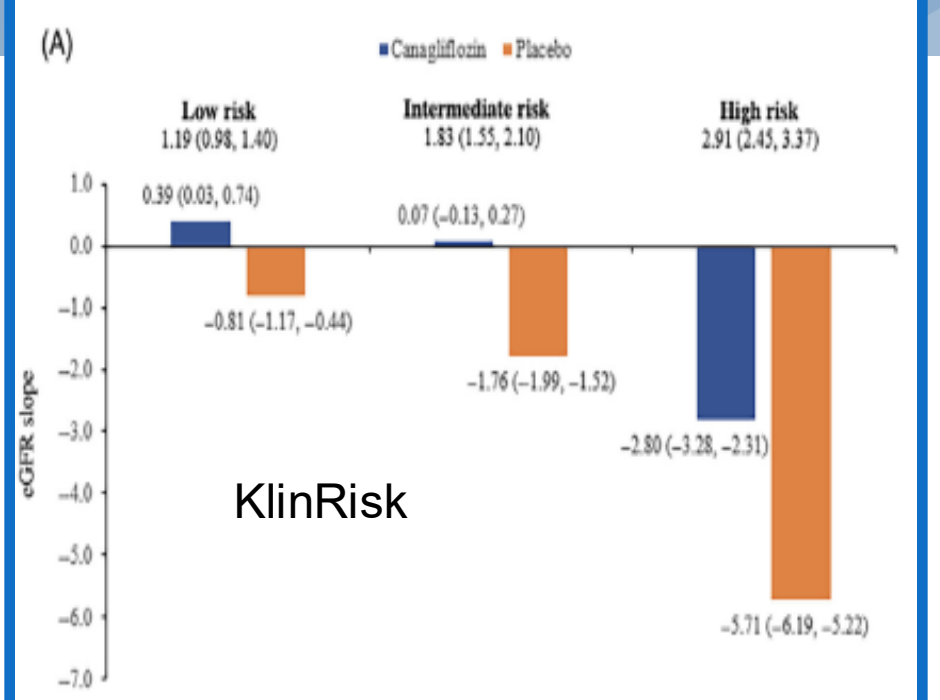
WILEY

ORIGINAL ARTICLE

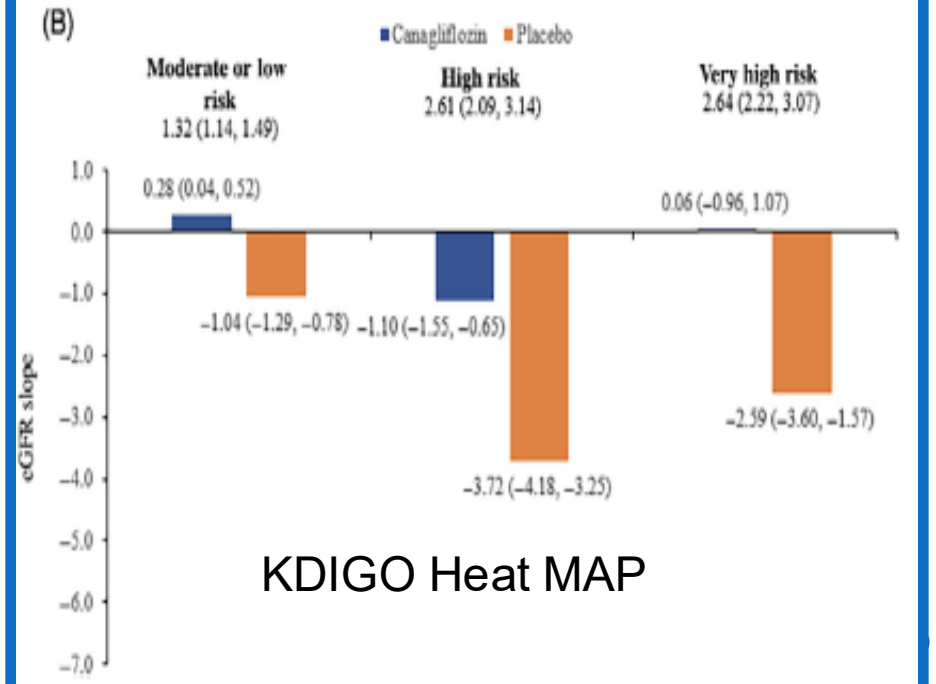
Machine learning for prediction of chronic kidney disease progression: Validation of the Klinrisk model in the CANVAS Program and CREDENCE trial

Navdeep Tangri MD[1,2] | Thomas W. Ferguson MSc[1,2] | Ryan J. Bamforth MSc[1] | Silvia J. Leon MSc[1] | Clare Arnott MD[3,4] | Kenneth W. Mahaffey MD[5] | Sradha Kotwal MD[3,6] | Hiddo J. L. Heerspink MD[7] | Vlado Perkovic MD[3] | Robert A. Fletcher MSc[3] | Brendon L. Neuen MD[3,8]





KlinRisk



KDIGO Heat MAP

Annals of Internal Medicine

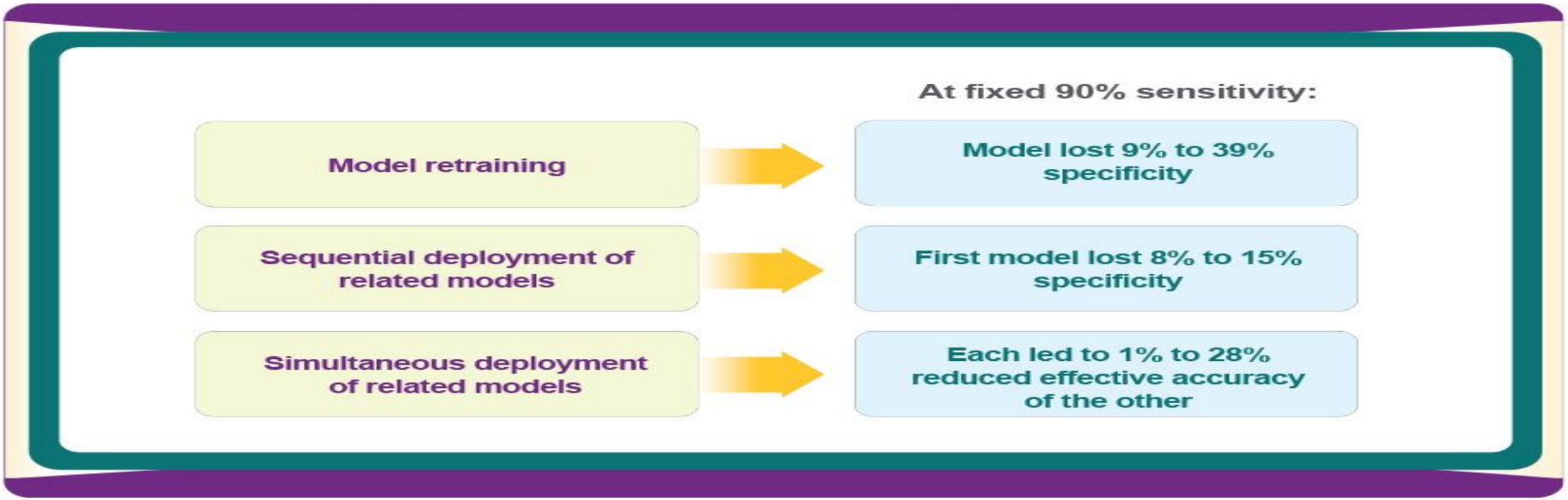
ORIGINAL RESEARCH

Implications of the Use of Artificial Intelligence Predictive Models in Health Care Settings

A Simulation Study

Akhil Vaid, MD; Ashwin Sawant, MD; Mayte Suarez-Farinas, PhD; Juhee Lee, MD; Sanjeev Kaul, MD; Patricia Kovatch, BS; Robert Freeman, RN; Joy Jiang, BS; Pushkala Jayaraman, MS; Zahi Fayad, PhD; Edgar Argulian, MD; Stamatios Lerakis, MD; Alexander W. Charney, MD, PhD; Fei Wang, PhD; Matthew Levin, MD, PhD; Benjamin Glicksberg, PhD; Jagat Narula, MD, PhD; Ira Hofer, MD; Karandeep Singh, MD, MMSc*; and Girish N. Nadkarni, MD, MPH*

How does performance of an artificial intelligence (AI) predictive model change with model retraining, or sequential or simultaneous deployment of related models?

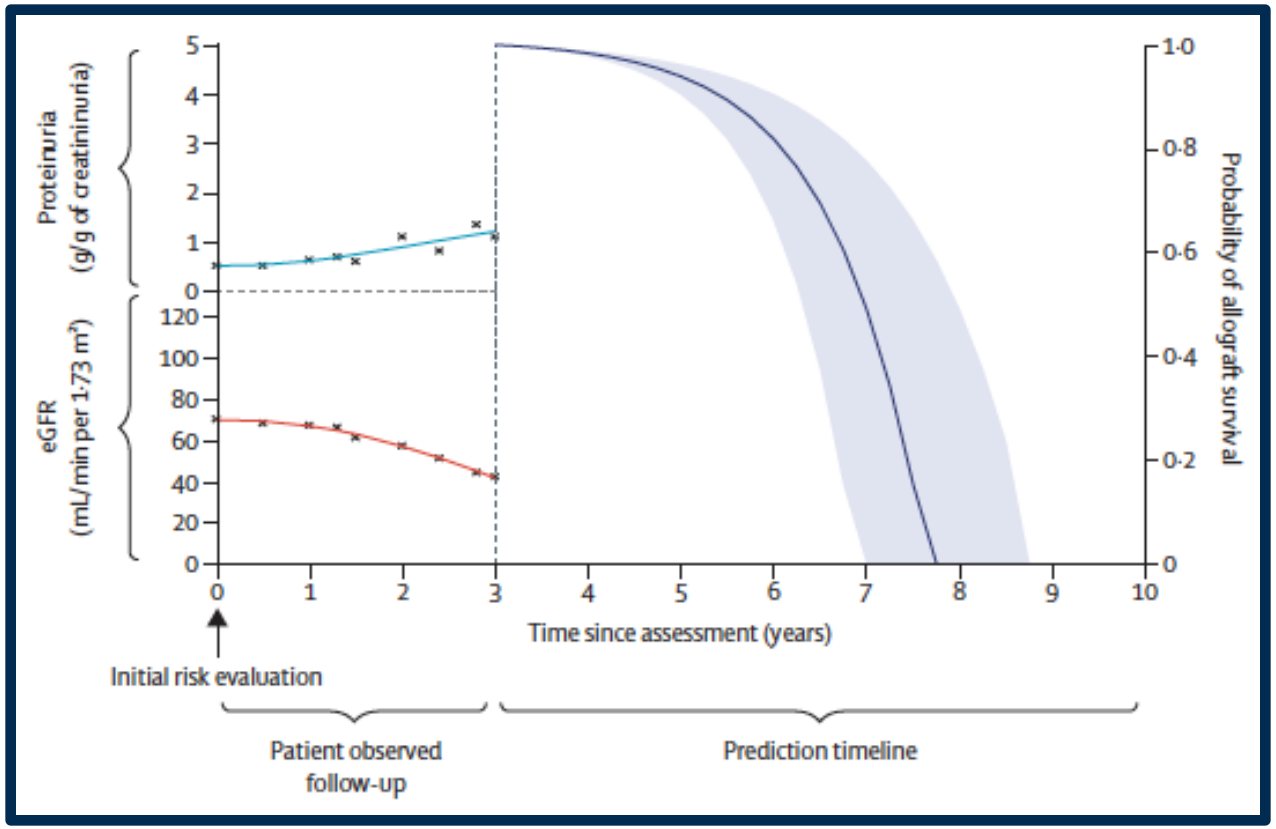


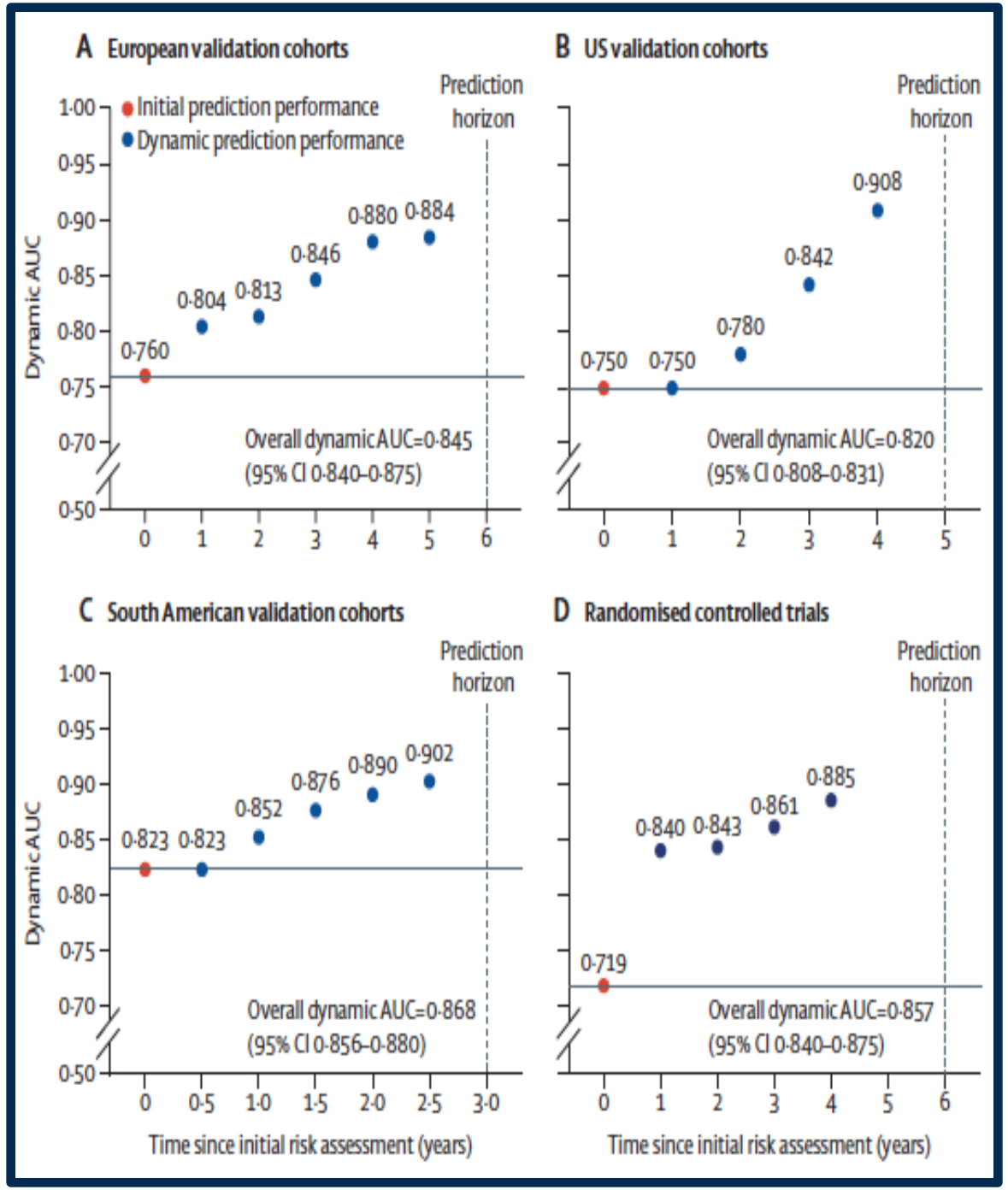
Annals of Internal Medicine

Vaid A, Sawant A, Suarez-Farinas M, et al. Implications of the use of artificial intelligence predictive models in health care settings. A simulation study. Ann Intern Med. 10 October 2023. [Epub ahead of print]. doi:10.7326/M23-0949
http://acpjournals.org/doi/10.7326/M23-0949

Dynamic prediction of renal survival among deeply phenotyped kidney transplant recipients using artificial intelligence: an observational, international, multicohort study

Marc Raynaud, Olivier Aubert*, Gillian Divard, Peter P Reese, Nassim Kamar, Daniel Yoo, Chen-Shan Chin, Élodie Bailly, Matthias Buchler, Marc Ladrière, Moglie Le Quintrec, Michel Delahousse, Ivana Juric, Nikolina Basic-Jukic, Marta Crespo, Helio Tedesco Silva Jr, Kamilla Linhares, Maria Cristina Ribeiro de Castro, Gervasio Soler Pujol, Jean-Philippe Empana, Camilo Ulloa, Enver Akalin, Georg Böhmig, Edmund Huang, Mark D Stegall, Andrew J Bentall, Robert A Montgomery, Stanley C Jordan, Rainer Oberbauer, Dorry L Segev, John J Friedewald, Xavier Jouven, Christophe Legendre, Carmen Lefaucheur, Alexandre Loupy*





An international observational study suggests that artificial intelligence for clinical decision support optimizes anemia management in hemodialysis patients

see commentary on page 259

Carlo Barbieri[1], Manuel Molina[2], Pedro Ponce[3], Monika Tothova[4], Isabella Cattinelli[1], Jasmine Ion Titapiccolo[1], Flavio Mari[1], Claudia Amato[1], Frank Leipold[1], Wolfgang Wehmeyer[1], Stefano Stuard[1], Andrea Stopper[1] and Bernard Canaud[1,5]

[1]Fresenius Medical Care, Bad Homburg, Germany; [2]Servicio de Nefrologia, Hospital Universitario Santa Lucía, Cartagena, Spain; [3]Fresenius Medical Care–Dialysis Center Lumiar, Lisbon, Portugal; [4]Fresenius Medical Care–Dialysis Center Motol, Prague, Czech Republic; and [5]Montpellier University I, UFR Medicine, Montpellier, France

Kidney International (2016) **90,** 422–429

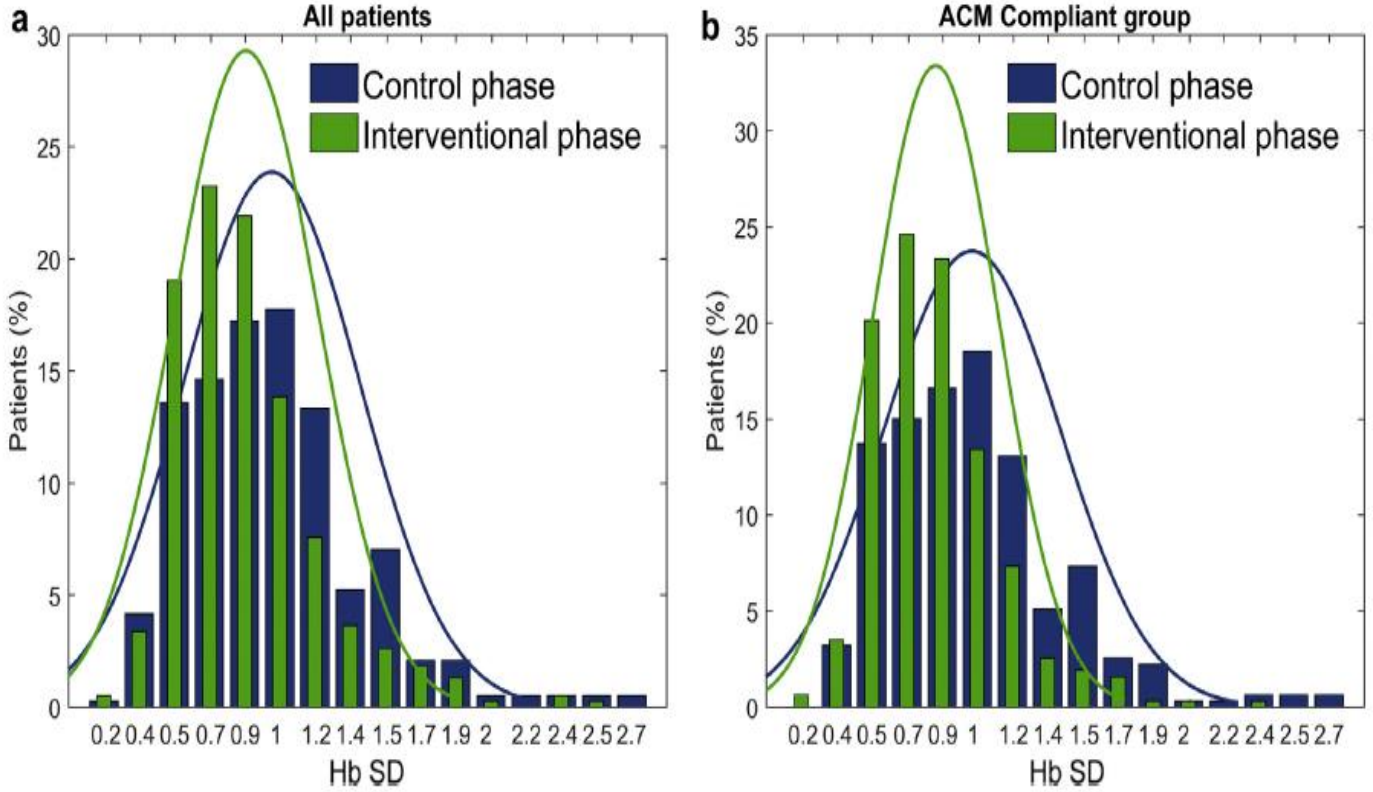


Table 5 | Parameters used by the hemoglobin predictive model

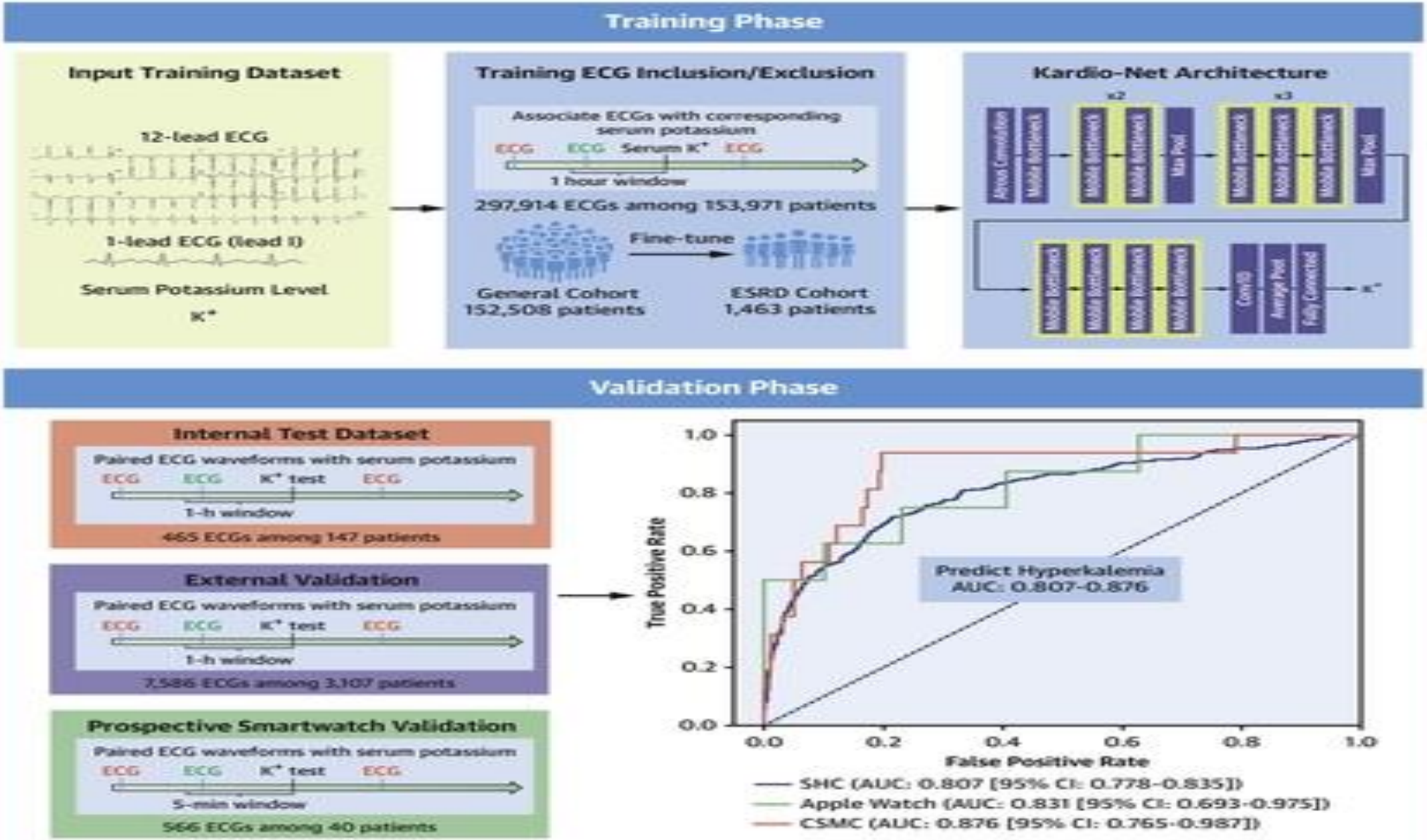
Parameter	Time
Sex	At admission
Height	At admission
Previous delta hemoglobin	Past month
Ferritin	Latest measurement
Transferrin saturation index	Latest measurement
Albumin	Latest measurement
Phosphate	Latest measurement
Leukocytes	Latest measurement
C-reactive protein	Latest measurement
Mean corpuscular volume	Latest measurement
Mean corpuscular hemoglobin	Latest measurement
Calcium	Latest measurement
Sodium	Latest measurement
Potassium	Latest measurement
Dry body weight	Latest measurement
Predialysis weight	Latest measurement
OCM Kt/V	Latest measurement
Darbepoetin doses	Past 90 days
Iron doses	Past 90 days

Lessons Learned…..

- We can predict lots of important endpoints – CKD Progression/ ESKD, Severe AKI, Transplant function
  - Is predicting Stage 1 AKI important ?
- Prediction and Prevention are different things
- Testing a static model is different than a dynamic (learning) model
  - What works in 2025 may not work in 2027.
  - What works in Chicago may not work in Madrid.

Other advanced technologies (e.g., wearables, home monitoring, implantables, generative AI, agentic AI, etc.)

CENTRAL ILLUSTRATION: AI-Enabled Smartwatch ECG for Potassium Monitoring



Chiu I-M, et al. JACC Clin Electrophysiol. 2024;10(12):2644-2654.

nature reviews nephrology

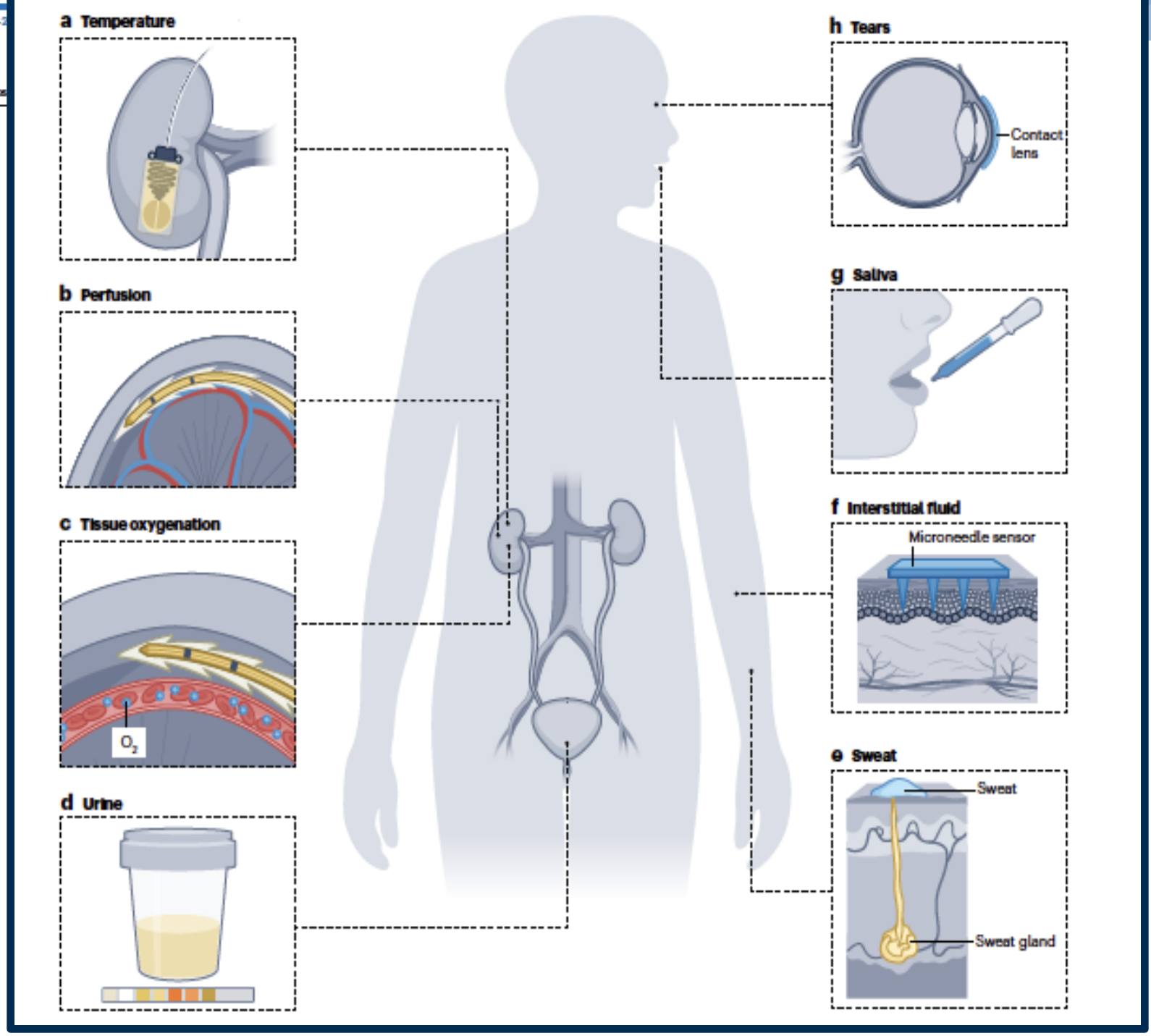
https://doi.org/10.1038/s41581-025-00961-2

Review article

Check for updates

Implantable bioelectronics and wearable sensors for kidney health and disease

Surabhi R. Madhvapathy[1,2,7], Soongwon Cho[1,7], Elisa Gessaroli[3,4,7], Eleonora Forte[4], Yirui Xiong[1,2], Lorenzo Gallon[4,5] & John A. Rogers[1,3,6,8]



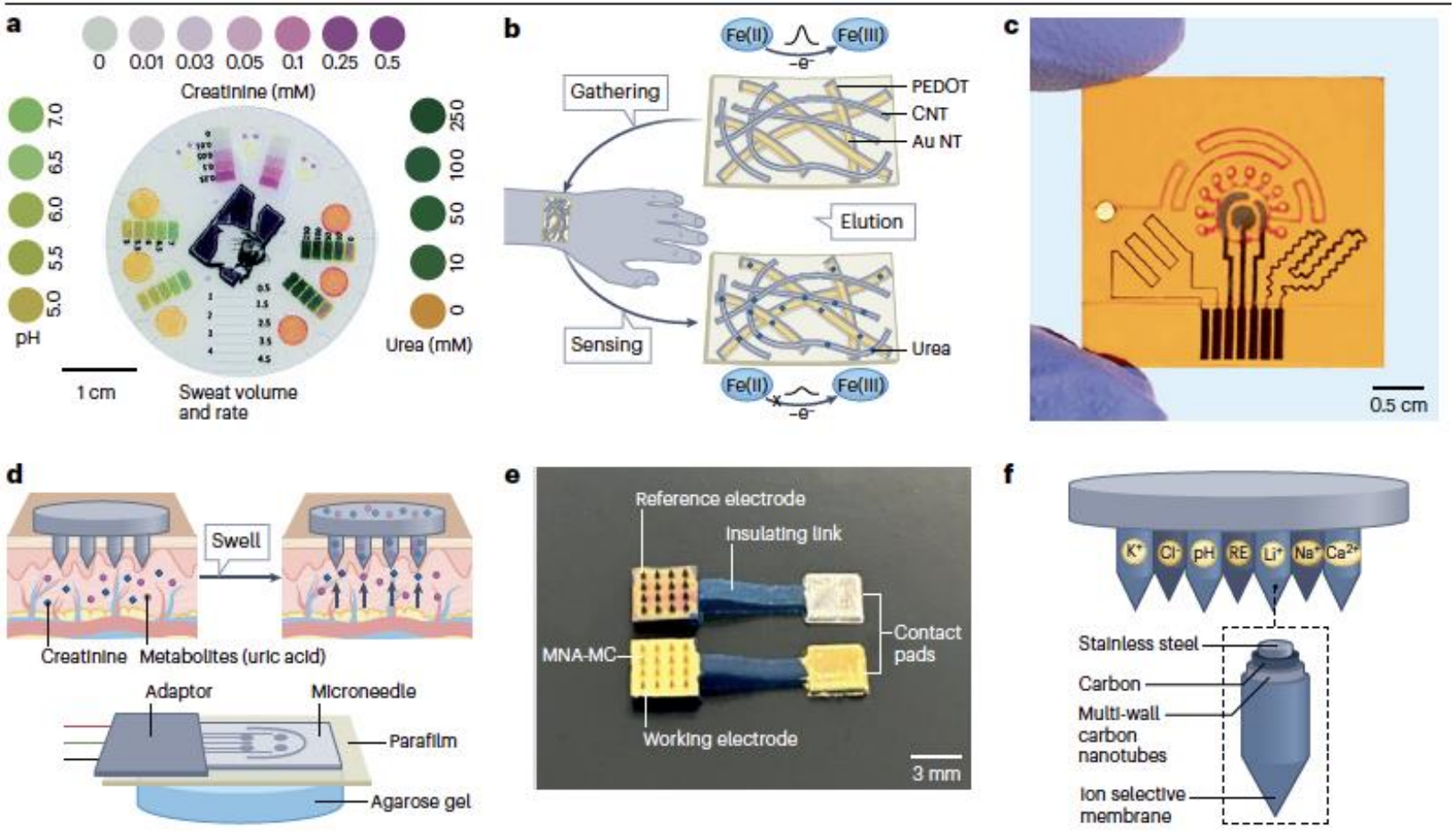
nature reviews nephrology
https://doi.org/10.1038/s41581-025-00961-2

Review article

Check for updates

Implantable bioelectronics and wearable sensors for kidney health and disease

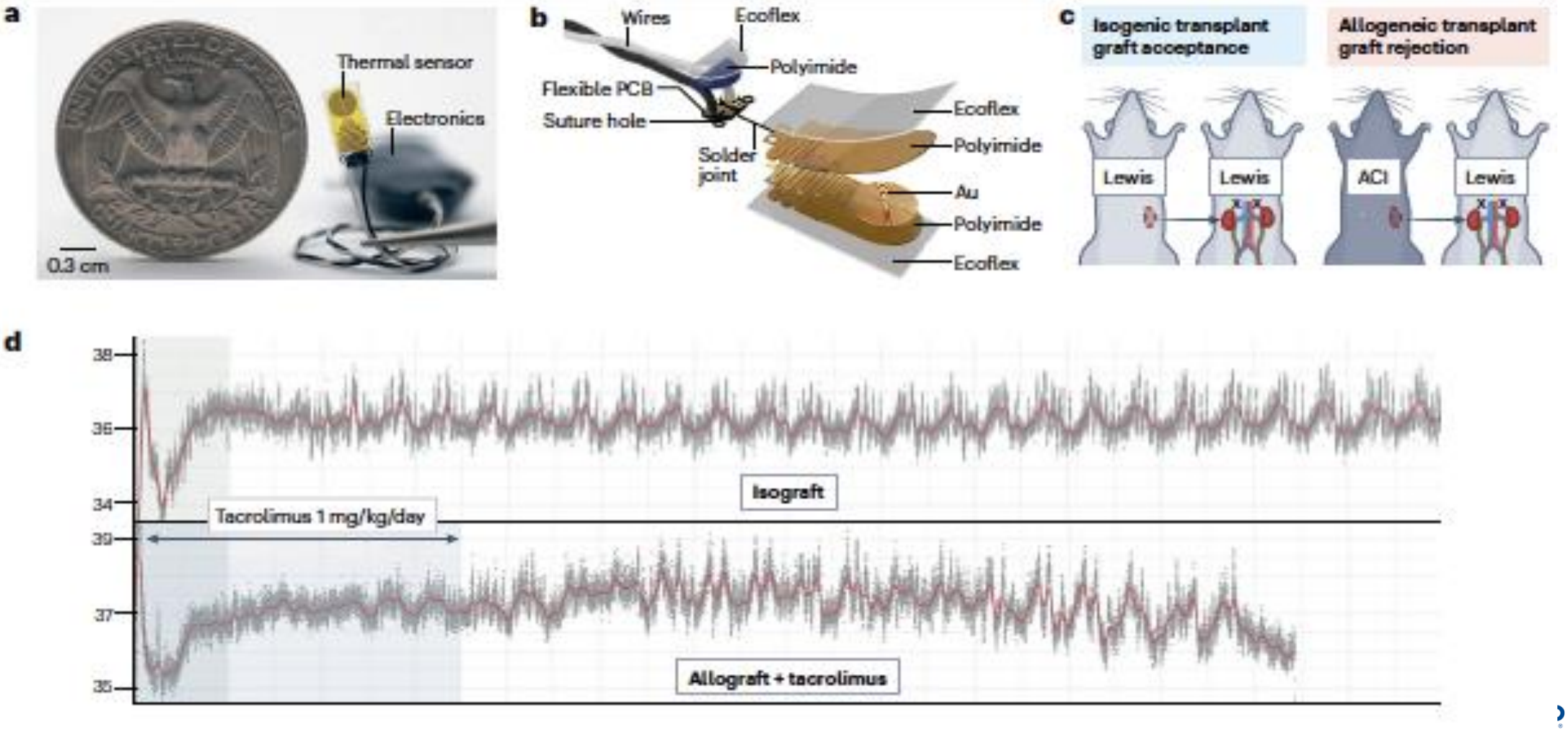
Surabhi R. Madhvapathy, Soongwon Cho, Elisa Gessaroli, Eleonora Forte, Yirui Xiong, Lorenzo Gallon & John A. Rogers

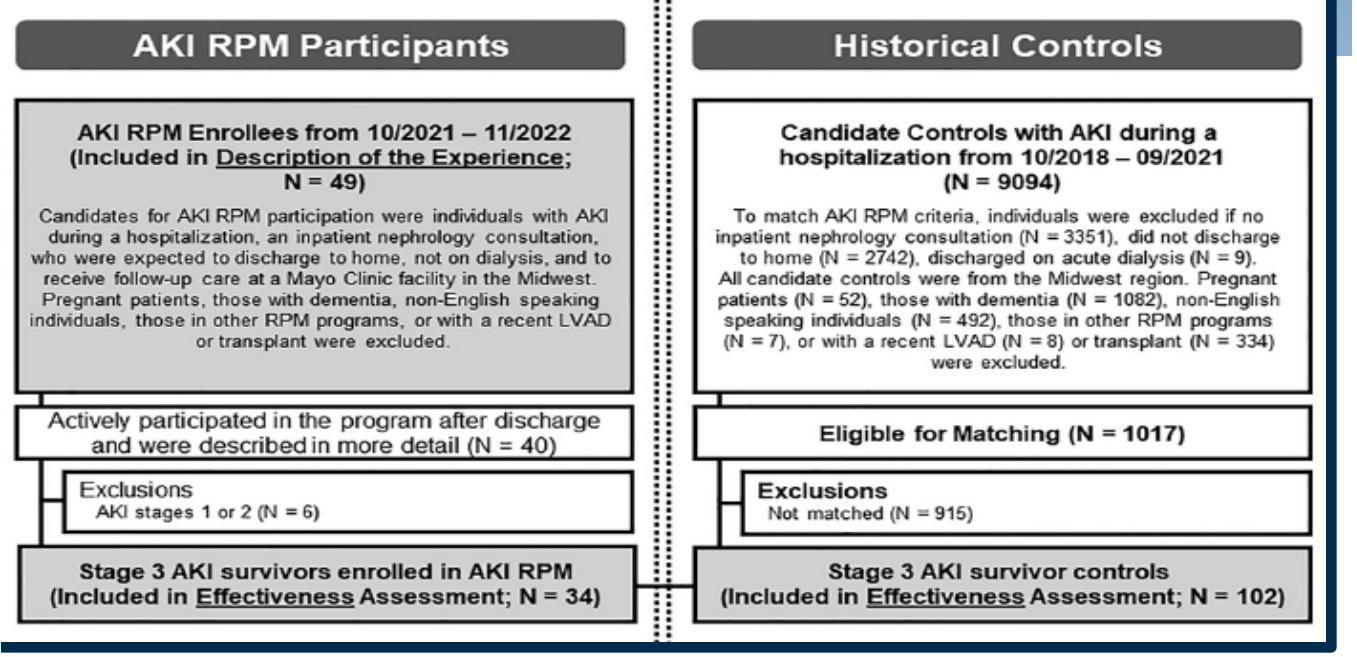


Solutes to measure

- Creatinine
- BUN
- Uric Acid
- Potassium
- Cystatin C

Temperature Monitoring for Transplanted Kidneys



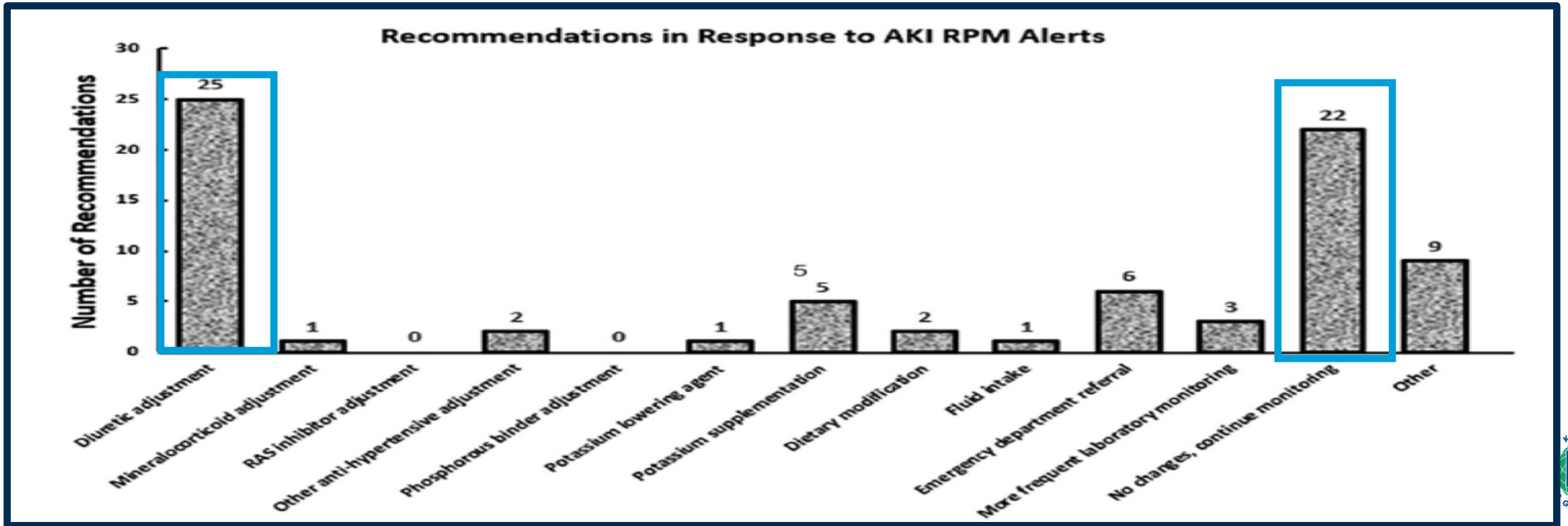


Original Research
Kidney Medicine

Acute Kidney Injury Survivor Remote Patient Monitoring: A Single Center's Experience and an Effectiveness Evaluation

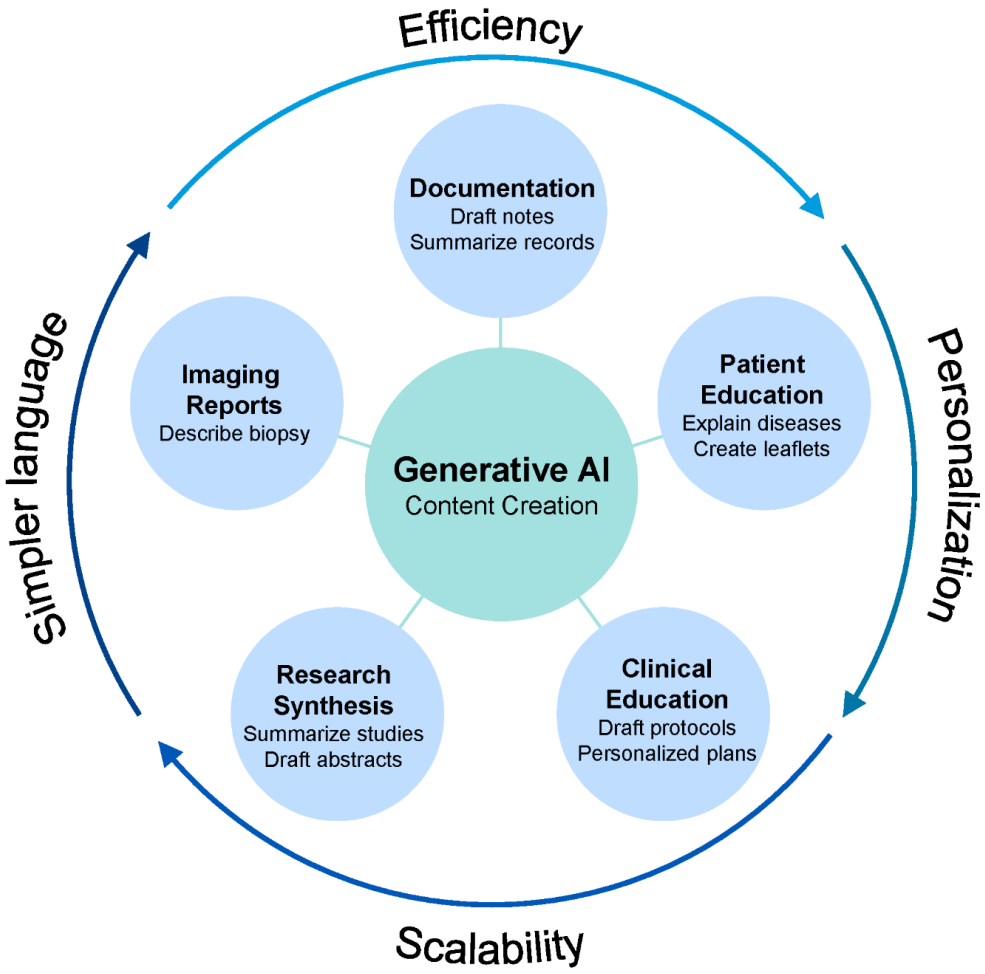
Mariam Charkviani, Andrea G. Kattah, Andrew D. Rule, Jennifer A. Ferguson, Kristin C. Mara, Kianoush B. Kashani, Heather P. May, Jordan K. Rosedahl, Swetha Reddy, Lindsey M. Philpot, and Erin F. Barreto

Home monitoring after AKI – if it worked you would know this paper



Generative AI

- Improve workflows
  - Converting dialogue/interactions into documentation
  - Generate referrals from notes
  - Improving patient “face time”
  - Less burn out
- Educational tools
  - Assist in talks/questions
  - “Hallucinations”



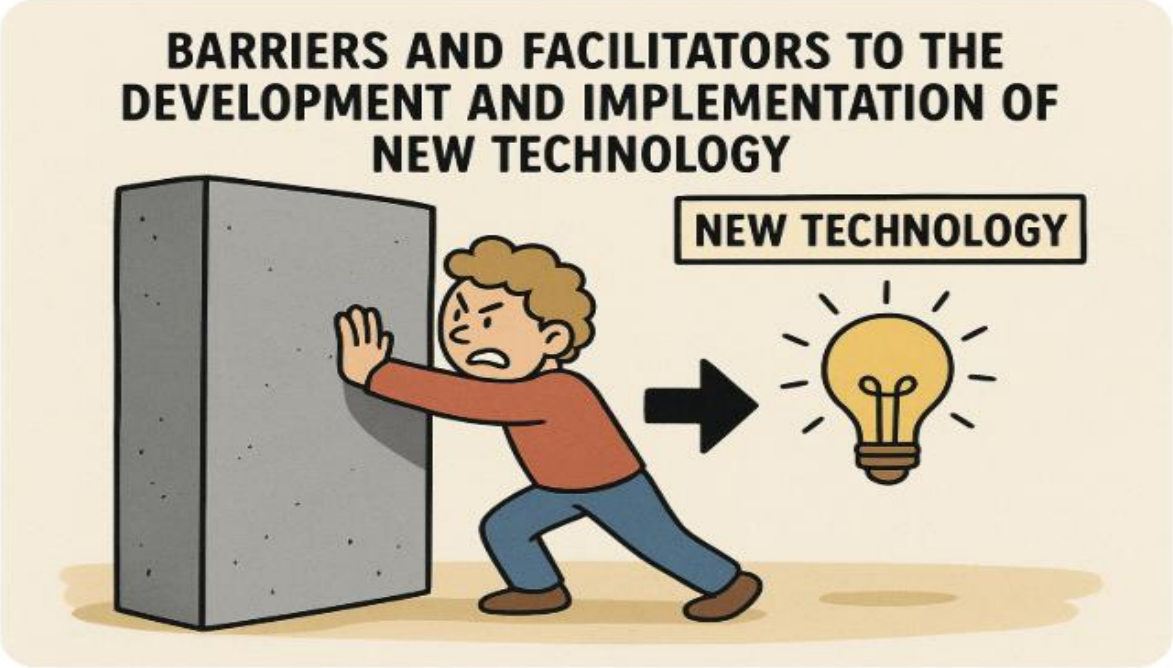
Agentic AI – I am not sure we are there yet…

- refers to artificial intelligence systems designed to autonomously plan, decide, and execute tasks with minimal human oversight

- Clinical decision support
- Patient triage
- Personalized treatment
- Predictive analytics
- Disease Detection
- Workflow –administrative support*

Barriers and facilitators to the development and implementation of new technology

show me a funny meme for this statement "Barriers and facilitators to the development and implementation of new technology"



AI is not available everywhere

Number of notable AI models by geographic area, 2003–24 (sum)

Source: Epoch AI, 2025 | Chart: 2025 AI Index report

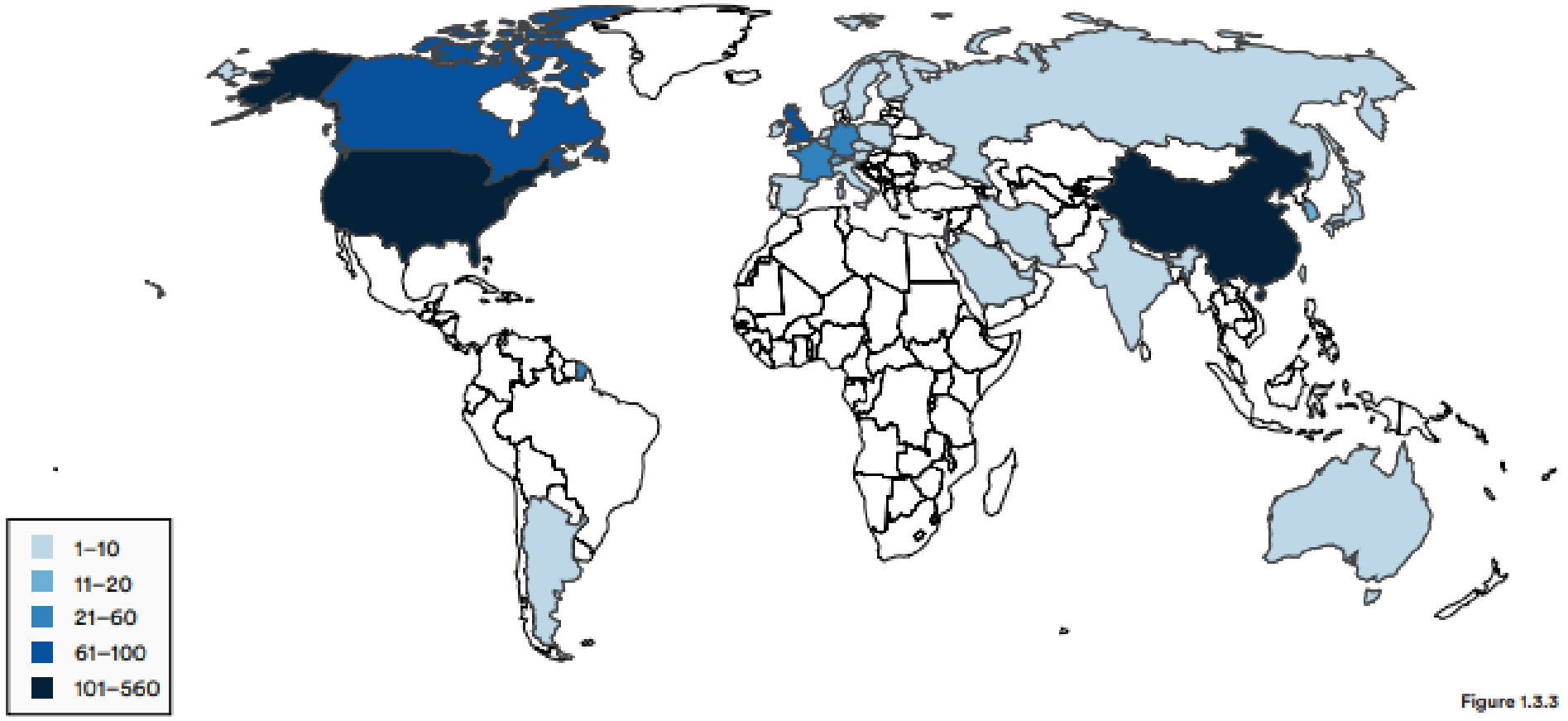


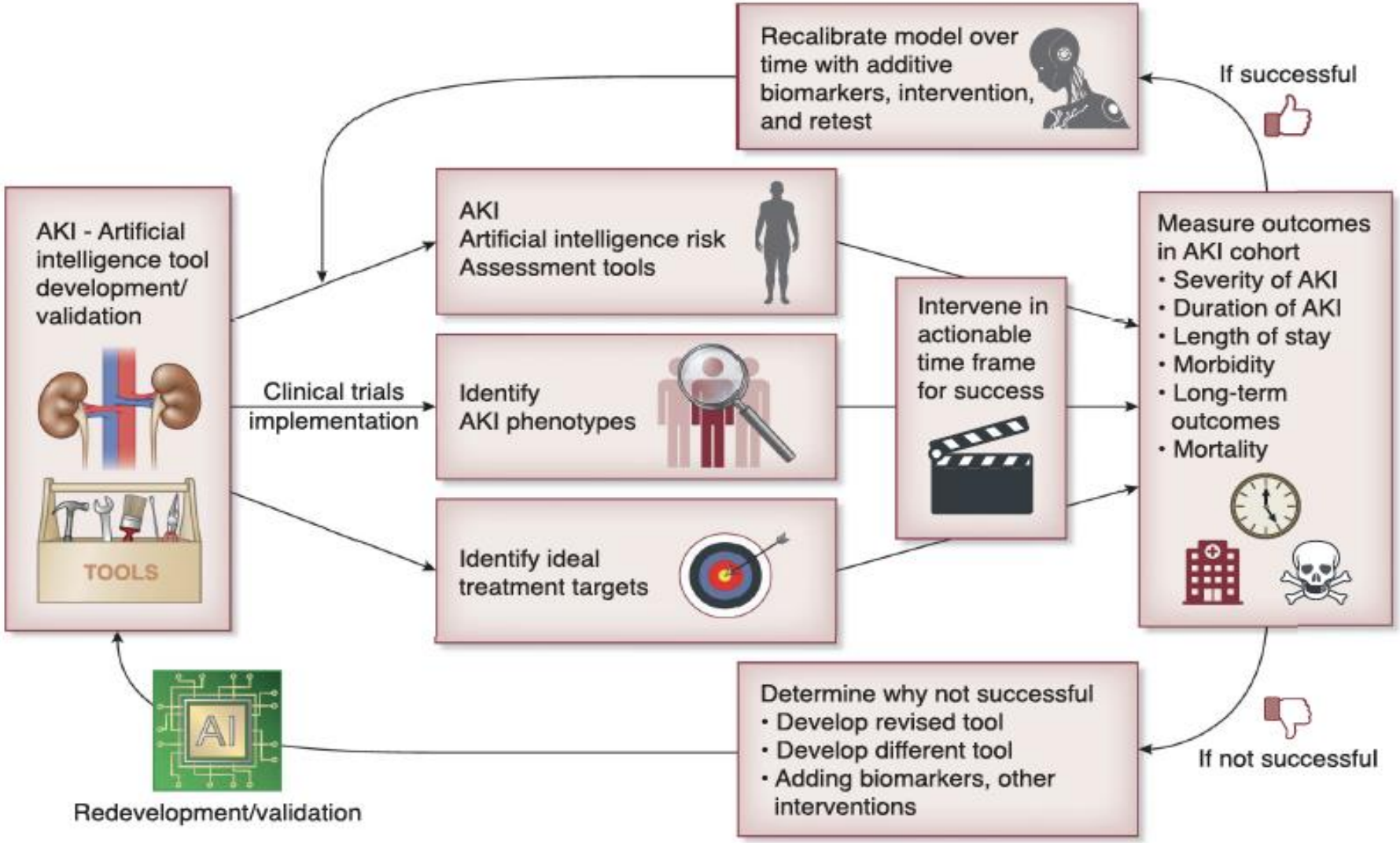
Figure 1.3.3

Stanford University Artificial Intelligence Index Report 2025

Other Barriers to Implementation

- Data Quality
  - Garbage in = Garbage out
- Bias
  - Diverse Multi-center data is the exception….
- Regulatory Issues
  - Locked vs. Unlocked data – Real World vs. Trials
- Clinical integration
  - Institutional set-up, maintenance, and adjustment are needed

Validation and Re-development….



Bajaj Koyner CJSAN 2023

CLIF

- **Open-source** research format for longitudinal ICU data science
- **Federated** research network-code is shared, not patient data
- Focused on a limited set of **minimum Common ICU data Elements**
- Accessible via **MIMIC-CLIF**

Barrier – Education / Training

Traditionally Nephrologists have not been at the forefront of implementation science, but I think this is changing….

Improve AI literacy

More hands-on training / curriculums

Where do I think we are headed?

AI IN HEALTH

Health tracker lives in your toilet and automatically scans pee

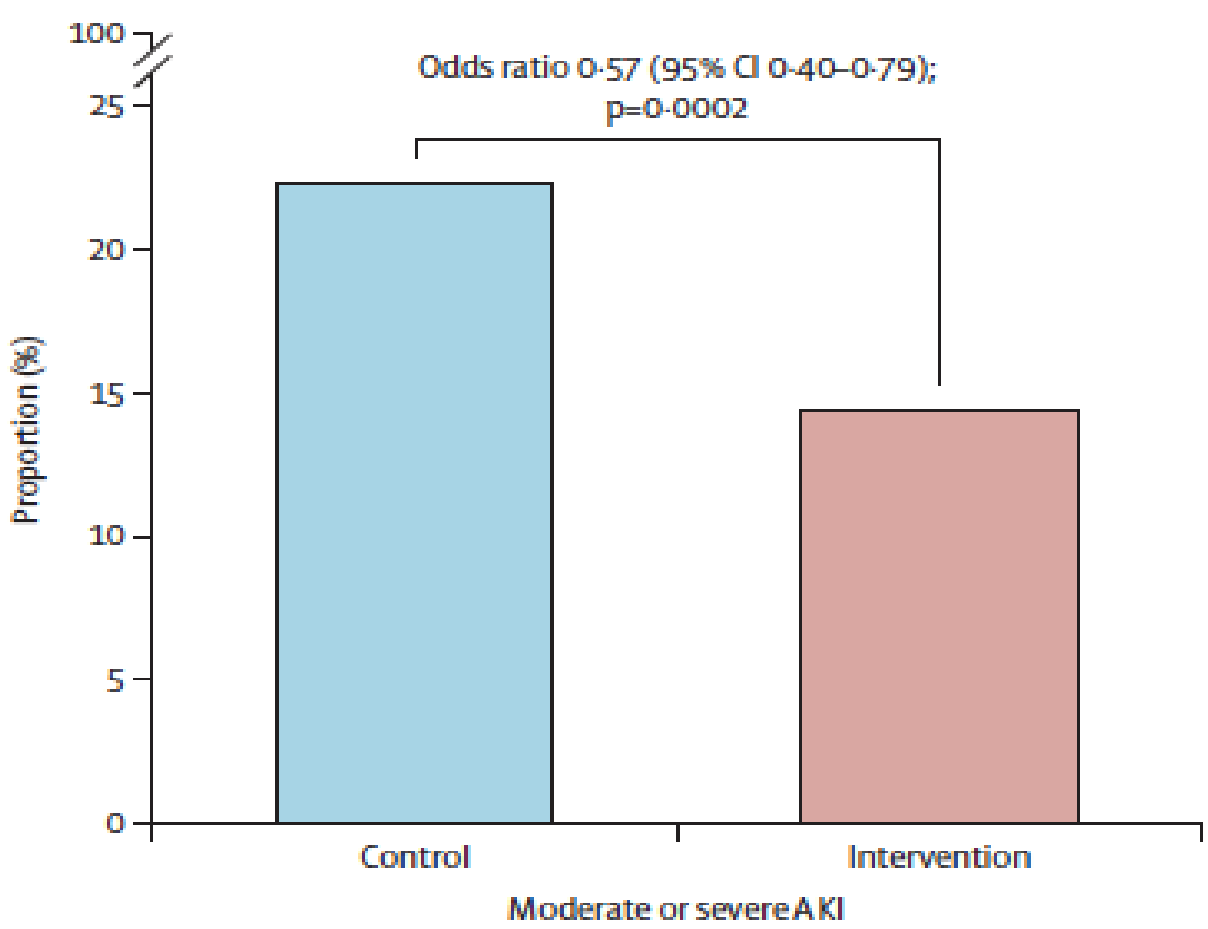
By Abhimanyu Ghoshal
November 22, 2024

- Integrated monitoring at home and from within the patient
  - Smart toilets to check for
  - Proteinuria
  - Hematuria
  - Drug levels
- (Non)-Invasive monitoring to optimize
  - Hemodynamics / Volume Status
  - Drug Dosing
  - Immuno-status
- All leading to continuous assessment and risk prediction for all things nephrology

Toto.com
abbvie.com

A preventive care strategy to reduce moderate or severe acute kidney injury after major surgery (BigpAK-2); a multinational, randomised clinical trial

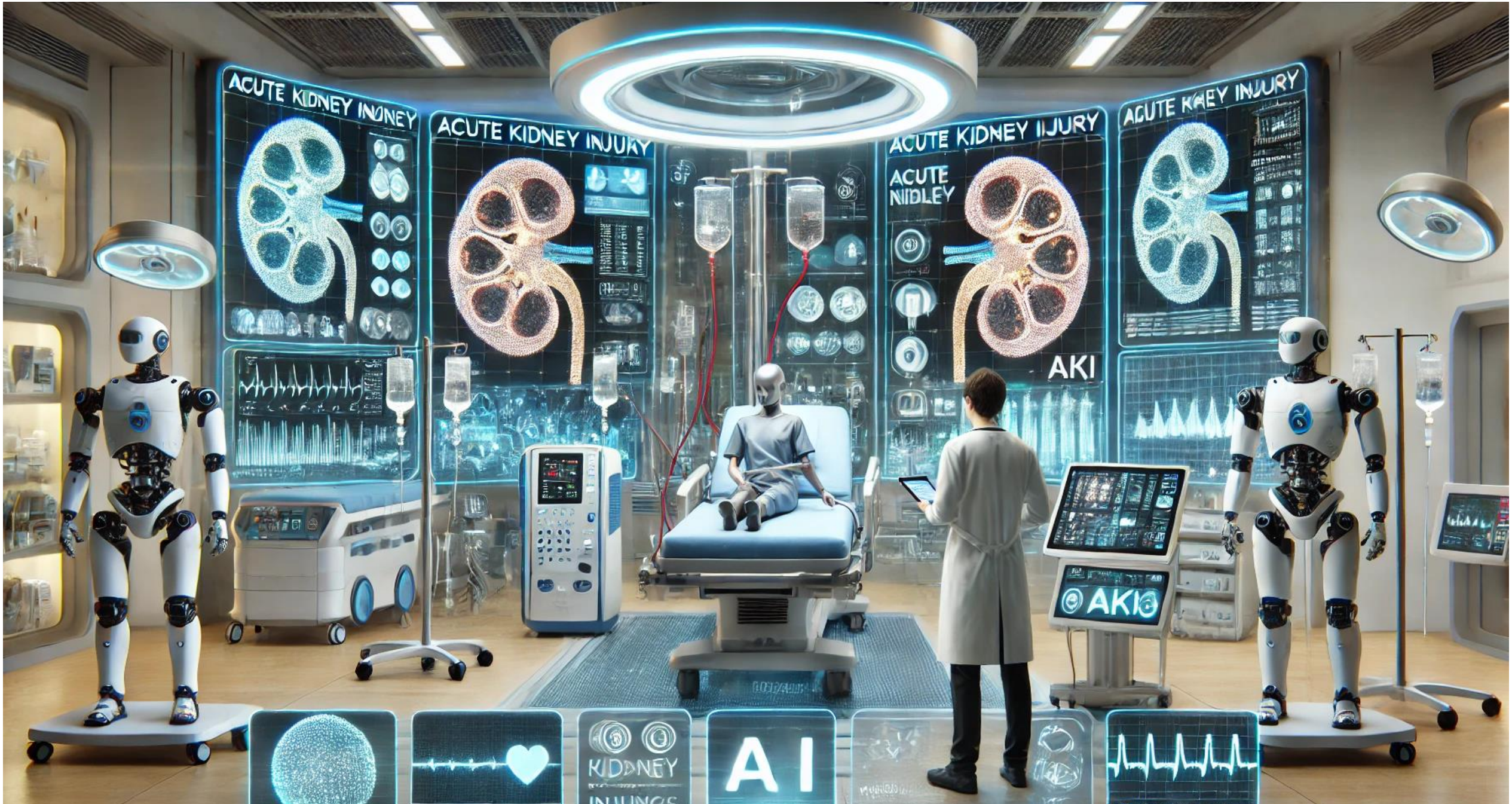
Alexander Zarbock, Marlies Ostermann, Lui Forni, Christian Bode, Lennart Wild, Christian Putensen, Diego Parise Roux, Elena Elías Martín, Christian Arndt, Tim Rahmel, Silvia de Rosa, Céline Monard, Antoine G Schneider, Adam Glass, Mona Jung-König, Stefano Romagnoli, James Gossage, Nuttha Lumlertgul, Jan Gerrit Haaker, Javier Ripollés-Melchor, Savino Spadaro, Antonio Siniscalchi, Emmanuel Futier, Lucie Aupetitgendre, Irene Romero Bhathal, Raquel García Álvarez, Alice Bernard, Peter Rosenberger, Carola Wempe, Mahan Sadjadi, Melanie Meersch, Karen Fischhuber, Rinaldo Bellomo, John A Kellum, Thilo von Groote, for the BigpAK-2 study group



- 1180 High-risk major surgery patients randomized to KDIGO bundle or usual care
- Reduced rates of Stage 2/3 AKI
- 268 (**47%**) in intervention arm had completed bundle (63% w/out glycemic) but only **5%** in the control arm (7% glycemic)

Conclusions

- AI is already here – but it needs refining
- Its in all aspects of Nephrology (AKI, Transplant, CKD, path….)
- Rigorous testing /validation of all AI is essential
- What works in Chicago may not work in Madrid or anywhere else
- Transparency
- Demystification of “black boxes”
- Clarity about what is in the algorithm
- Ethical oversight is needed (a whole separate talk)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