Intelligence Artificielle et Rythmologie : le futur c'est maintenant

Apport de l'IA en Rythmologie en 2025 : vraiment pertinente cliniquement au lit du patient ?

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Avec le parrainage de la SFC

Conflict of Interest

- CHIESI: adjudication committee
- J&J: scientific committee
- Patent processing for AI based algorithm in LQTS

nature medicine

REVIEW ARTICLE

https://doi.org/10.1038/s41591-021-01614-0

AI in health and medicine

Pranav Rajpurkar[1,4], Emma Chen[2,4], Oishi Banerjee[2,4] and Eric J. Topol[3]

Artificial intelligence (AI) is poised to broadly reshape medicine, potentially improving the experiences of both clinicians and patients. We discuss key findings from a 2-year weekly effort to track and share key developments in medical AI. We cover prospective studies and advances in medical image analysis, which have reduced the gap between research and deployment. We also address several promising avenues for novel medical AI research, including non-image data sources, unconventional problem formulations and human–AI collaboration. Finally, we consider serious technical and ethical challenges in issues spanning from data scarcity to racial bias. As these challenges are addressed, AI's potential may be realized, making healthcare more accurate, efficient and accessible for patients worldwide.

Nature Medecine.
2022;28: 31–38

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- Interprétation ECG (standard & longue durée)
- Mesures
- Identification de choses que l’on ne voit pas
- Prédiction

Performance of a Convolutional Neural Network and Explainability Technique for 12-Lead Electrocardiogram Interpretation

JAMA Cardiol. 2021;6:1285-95

J. Weston Hughes, BA; Jeffrey E. Olgin, MD; Robert Avram, MD, MSc; Sean A. Abreau, ScM; Taylor Sittler, MD;
Kaahan Radia, BA; Henry Hsia, MD; Tomos Walters, MD; Byron Lee, MD;
Joseph E. Gonzalez, PhD; Geoffrey H. Tison, MD, MPH

(n=32,576 patients; 91,440 ECGs)

eTable 2. F1 Score of the Convolutional Neural Network on 38 Diagnostic Classes Compared Against the Cardiologist Clinical Diagnoses in the Hold-Out Test Data Set

Diagnostic Class **Rhythm**	Frequency	F1 score
Sinus	57,186	0.977
Atrial Fibrillation	6,572	0.909
Atrial Flutter	1,406	0.714
Ectopic Atrial Rhythm*	514	0.403
Atrial Tachycardia*	194	0.225
Ventricular Tachycardia*	33	0.465
Junctional Rhythm*	489	0.491
Supraventricular Tachycardia*	308	0.651
Bigeminy*	248	0.698
Premature Ventricular Complex	3,930	0.803
Premature Atrial Complex	4,633	0.756
Ventricular Paced	2,443	0.879
Atrial Paced†	557	0.822
Rhythm Diagnosis Average‡		**0.930**

Conduction		
AV Block 1st Degree	5,608	0.828
AV Block 2nd Degree Mobitz 1*	182	0.543
Left Bundle Branch Block	2,026	0.807
Right Bundle Branch Block	7,605	0.871
Left Anterior Fascicular Block	3,520	0.721
Left Posterior Fascicular Block*	372	0.384
Bifascicular Block†	1,197	0.739
Nonspecific Intraventricular Conduction Delay	1,695	0.502
Right Axis Deviation	2,768	0.695
Left Axis Deviation	5,951	0.714
Right Superior Axis*	308	0.670
Prolonged QT	6,700	0.637
Wolff Parkinson White*	140	0.793
Conduction Diagnosis Average‡		**0.740**

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Table 1. Performance of the CNN on 38 Diagnostic Classes Compared With Cardiologist Clinical Diagnoses in the Holdout Test Data Set (N = 32 576 Patients; 91 440 ECGs)

Diagnostic class	Frequency	CNN AUC (95% CI)	Specificity[a]	Sensitivity[b]
Rhythm				
Sinus	57 186	0.995 (0.994-0.995)	0.993	0.990
Prolonged QT	6700	0.959 (0.958-0.961)	0.894	0.888

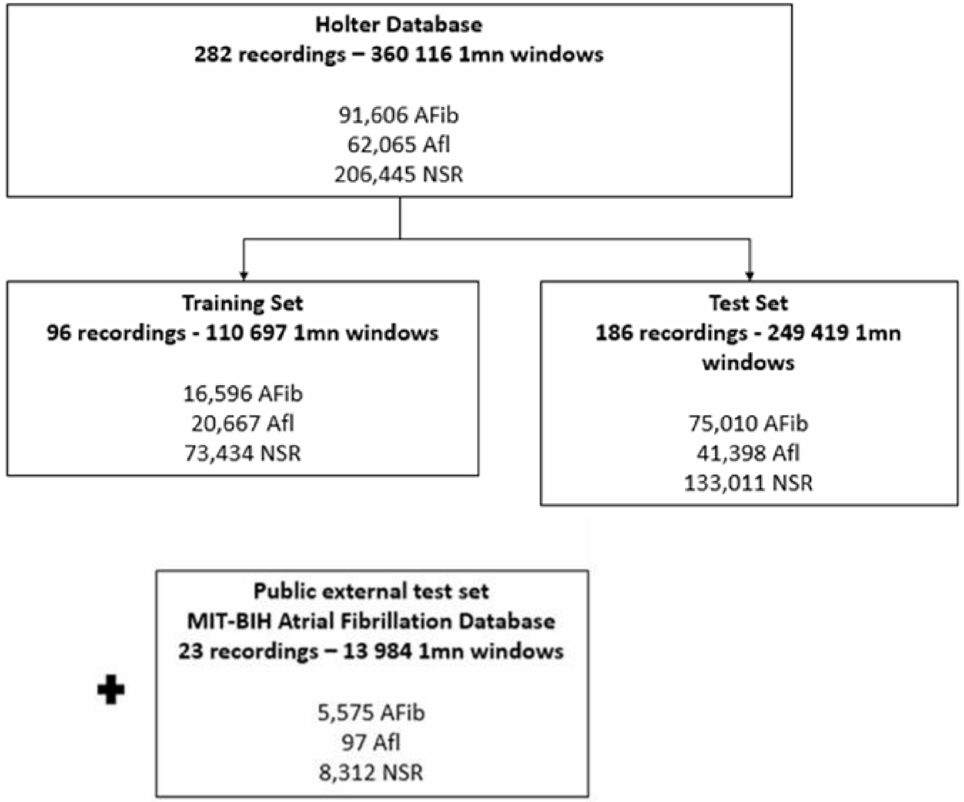
Table 2. Performance of the CNN, Cardiologist Diagnosis, and MUSE Diagnosis[a] on 38 Diagnostic Classes Compared Against the Committee Consensus Diagnosis (N = 328)

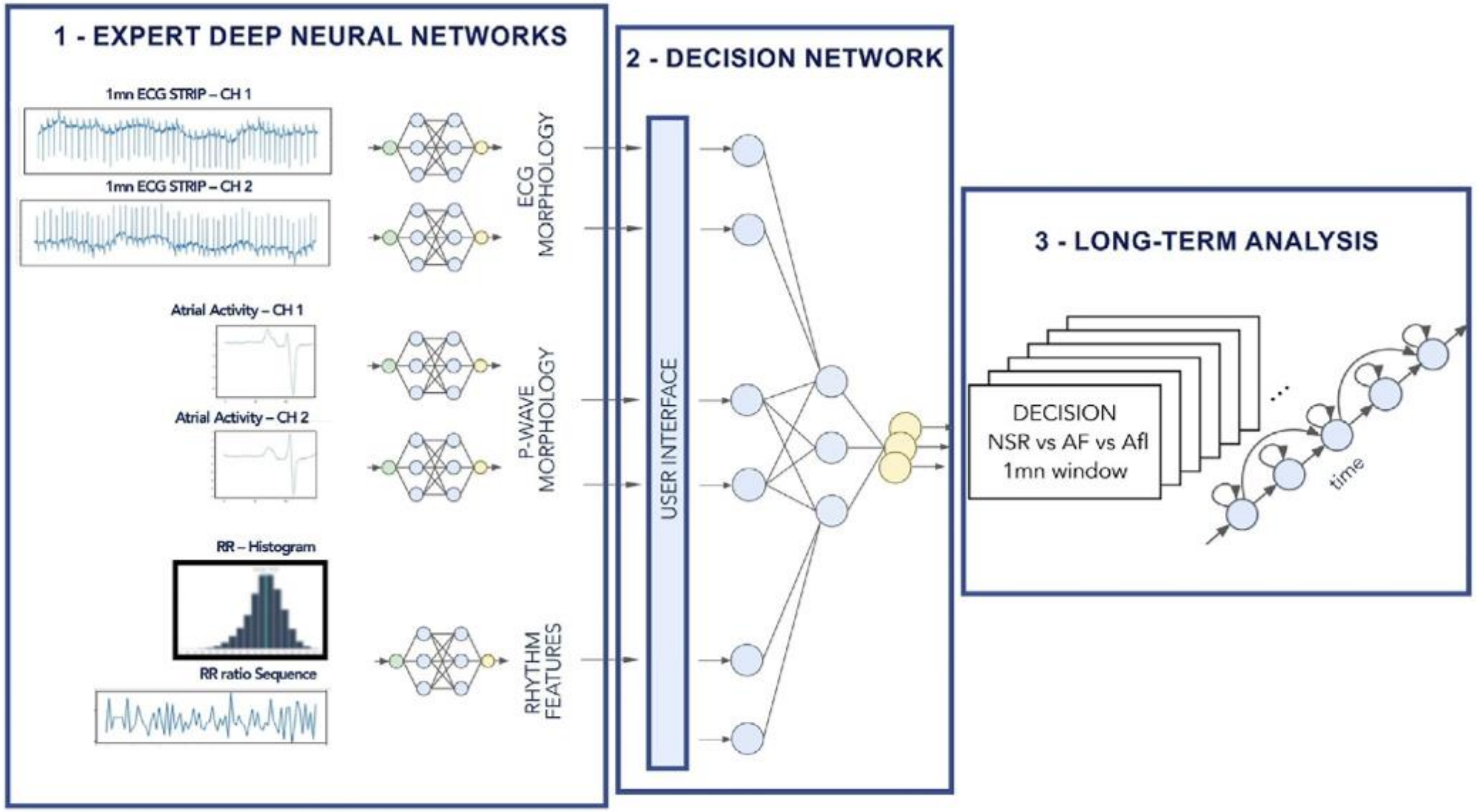
Diagnostic class	Frequency	CNN AUC (95% CI)	CNN F1 score[b]	Cardiologist clinical F1 score	MUSE F1 score	Cardiologist-fixed specificity[c]	CNN sensitivity	Cardiologist clinical sensitivity
Rhythm								
Sinus	228	0.856 (0.810-0.888)	0.849	0.818	0.784	0.940	0.750	0.711
Prolonged QT	26	0.860 (0.795-0.918)	0.500	0.360	0.415	0.950	0.423	0.346

A deep learning modular ECG approach for cardiologist assisted adjudication of atrial fibrillation and atrial flutter episodes

Heart Rhythm O2
2024;5:862–872

Quentin Fleury, MSc,[1,4] Rémi Dubois, PhD,[1] Sylvain Christophle-Boulard, MSc,[4] Fabrice Extramiana, MD, PhD,[2,3] Pierre Maison-Blanche, MD[2]





External cohort validation: MIT-BIH AF database

F1-score = 97% for NSR and 96% for ATA

Artificial intelligence for direct-to-physician reporting of ambulatory electrocardiography

Nature Med. 2025;31:925-31

- Annotation of 14,606 individual ambulatory ECG recordings (14±10 days) by certified ECG technicians (n = 167) and DeepRhythmAI
- Random sample of 5,235 rhythm events by one of 17 cardiologist consensus panels

Table 1 | Performance of DeepRhythmAI and ECG technicians compared to the consensus panel of cardiologists for critical arrhythmias

	Accuracy (95% CI), %		True-positive rate/ sensitivity, % (95% CI)		True-negative rate/ specificity, % (95%CI)		PPV, % (95% CI)		NPV, %(95% CI)		F1 score, %	
	AI	Technician	AI	Technician	AI	Technician	AI	Technician	AI	Technician	AI	Technician
Overall average critical arrhythmias	98.1 (97.9–98.2)	98.4 (98.1–98.5)	**98.6 (97.7–99.4)**	80.3 (77.3–83.3)	98.1 (97.9–98.2)	**99.2 (99.0–99.3)**	71.3 (68.5–73.9)	**82.7 (79.4–85.6)**	**99.9 (99.9–100)**	99.1 (98.9–99.2)	82.7 (80.9–84.5)	81.5 (79.0–83.6)
VT≥10s	98.2 (98.1–98.3)	99.5 (99.4–99.6)	**98.0 (94.8–100)**	64.4 (54.9–73.8)	98.2 (98.1–98.3)	**99.8 (99.7–99.8)**	27.2 (22.8–32.3)	**67.7 (58.2–76.6)**	**99.98 (99.96–100)**	99.7 (99.6–99.8)	42.6 (37.1–48.6)	**66.0 (57.4–73.2)**
AF≥30s	97.2 (96.5–97.9)	97.4 (96.6–98.0)	**99.1 (97.7–100)**	90.5 (86.8–94.0)	96.9 (96.2–97.7)	**98.4 (97.8–98.9)**	82.3 (77.8–86.8)	88.9 (84.7–92.6)	**99.9 (99.7–100)**	98.6 (98.0–99.2)	90.0 (87.1–92.7)	89.7 (86.7–92.3)
SVT≥30s	97.4 (97.1–97.9)	96.1 (95.5–96.7)	**97.3 (94.9–99.1)**	62.9 (56.6–69.3)	97.4 (97.0–97.9)	98.1 (97.7–98.4)	70.6 (65.9–75.7)	65.8 (59.3–72.2)	**99.8 (99.7–99.9)**	97.8 (97.2–98.3)	**81.8 (78.3–75.2)**	64.3 (58.7–69.8)
Asystole≥3.5s	98.5 (98.2–98.7)	**99.2 (99.0–99.4)**	**100 (100–100)**	80.6 (75.0–86.0)	98.4 (98.2–98.6)	**99.8 (99.7–99.9)**	65.7 (60.5–70.4)	**91.2 (87.8–95.6)**	**100 (100–100)**	99.4 (99.2–99.6)	79.2 (75.4–82.6)	85.8 (82.1–89.5)
Third-degree AV block	99.3 (99.2–99.4)	99.5 (99.3–99.6)	**96.4 (92.5–99.2)**	52.6 (44.0–61.6)	99.3 (99.2–99.4)	**99.9 (99.8–99.9)**	51.2 (44.6–48.2)	**76.3 (67.1–85.4)**	**100 (99.9–100)**	99.6 (99.5–99.7)	66.9 (61.2–72.8)	62.2 (53.9–70.0)

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Artificial Intelligence–Enabled Assessment of the Heart Rate Corrected QT Interval Using a Mobile Electrocardiogram Device

Circulation. 2021; 143:1274–1286

John R. Giudicessi, MD, PhD*
Matthew Schram, PhD*
J. Martijn Bos, MD, PhD
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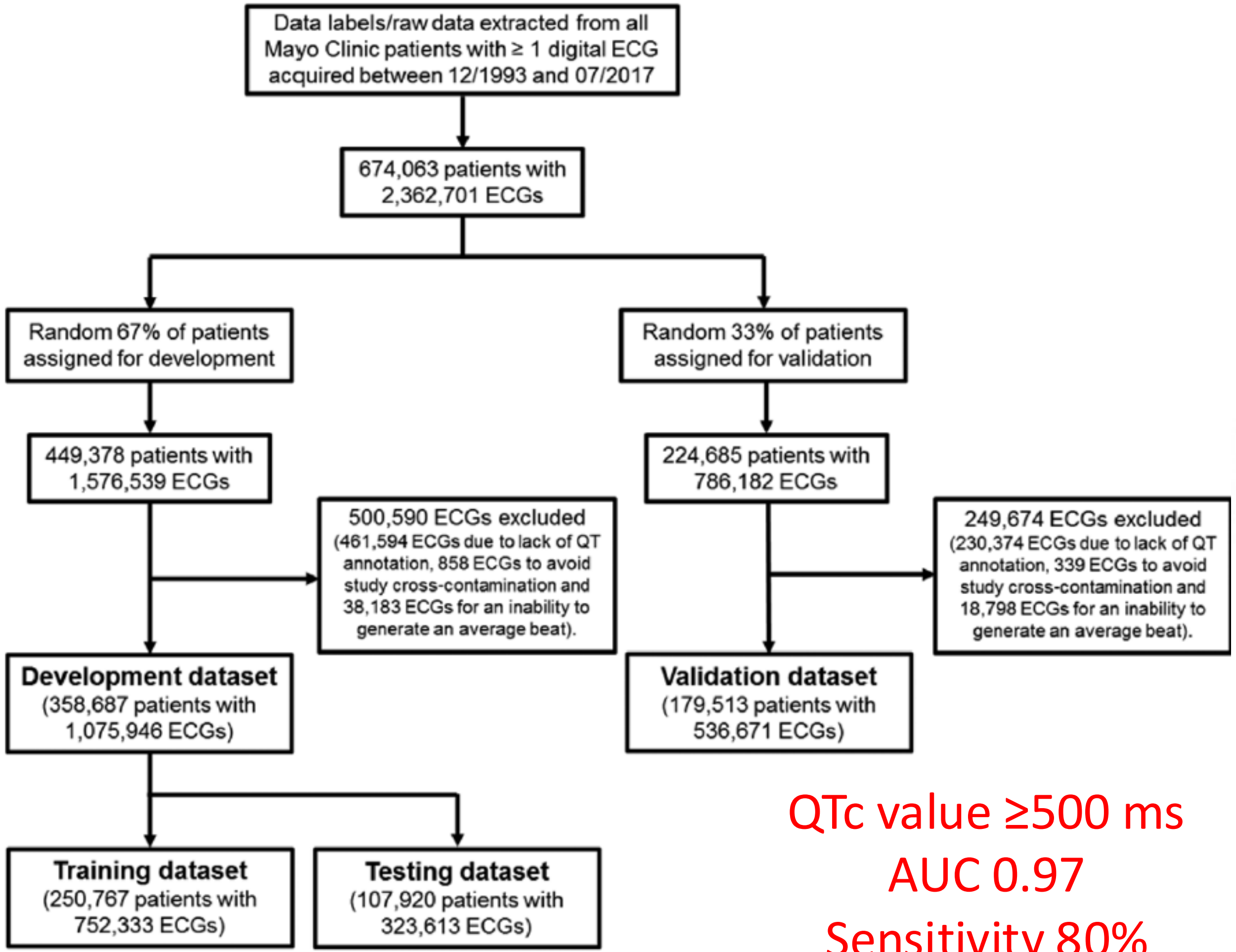
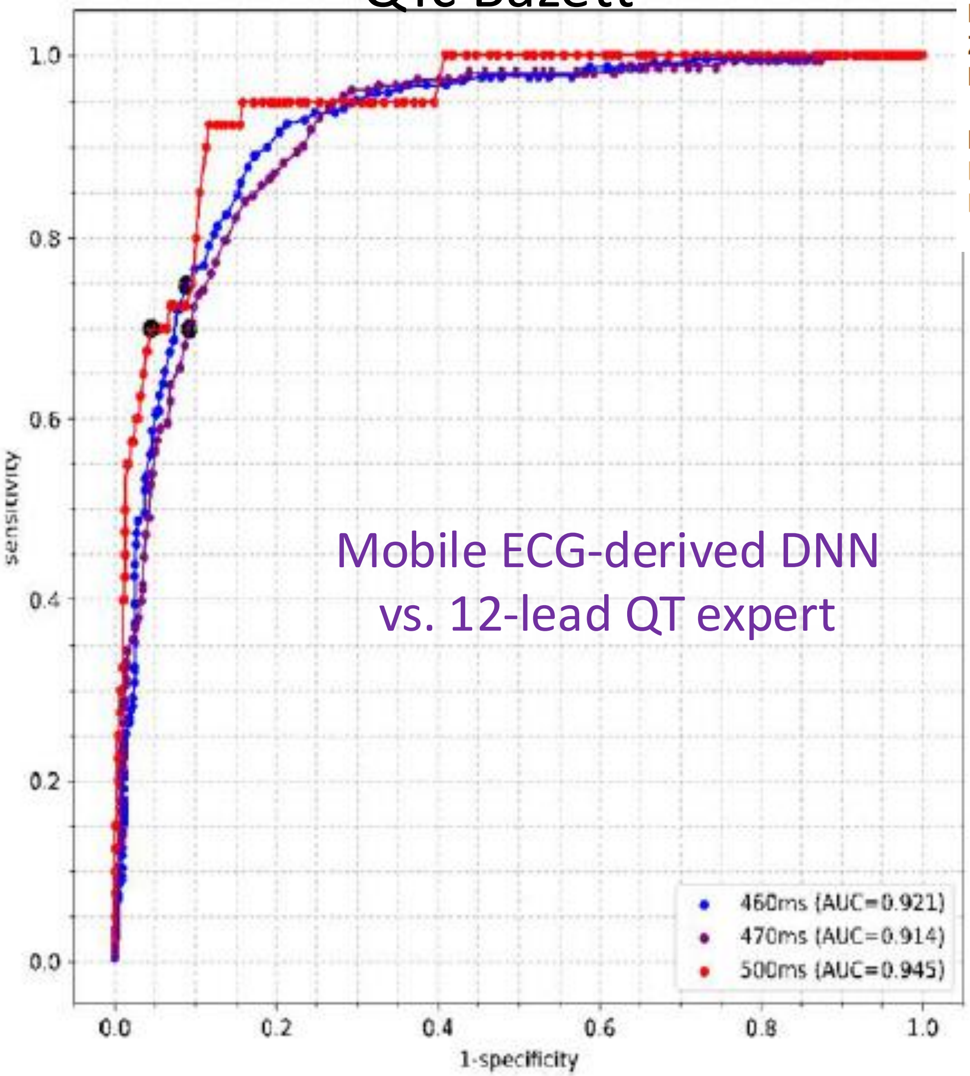


QTc Bazett



QTc value ≥500 ms
AUC 0.97
Sensitivity 80%
Specificity 94.4%

Collège National des Cardiologues des Hôpitaux

Avec le parrainage de la SFC

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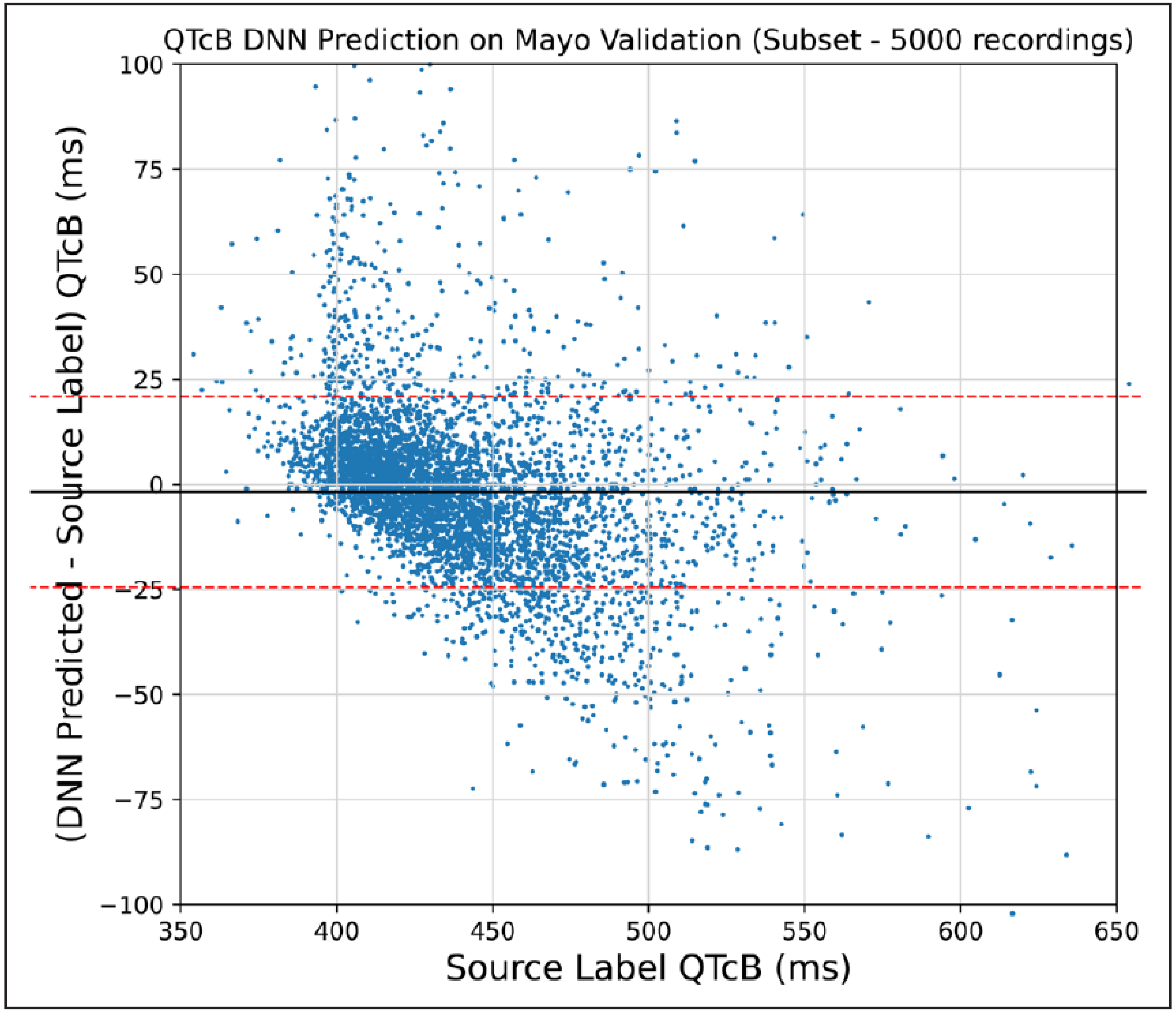

2-lead ECG DNN
vs.
technician-/physician
-overread 12-lead ECG

CONCLUSIONS: Using smartphone-enabled electrodes, an AI DNN can accurately the QTc of a standard 12-lead ECG. QTc estimation from an AI-enabled mECG device may provide a cost-effective means of screening for both acquired and congenital long QT syndrome in a variety of clinical settings **where standard 12-lead electrocardiography is not accessible or cost-effective.**

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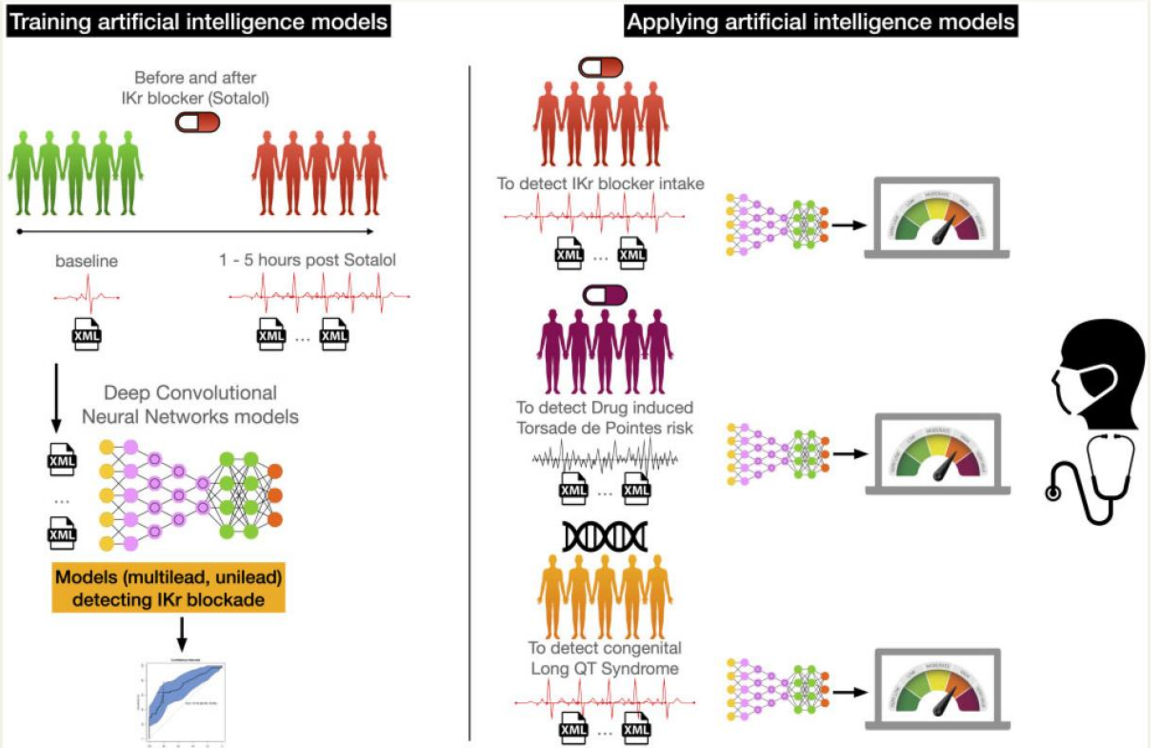
Deep learning analysis of electrocardiogram for risk prediction of drug-induced arrhythmias and diagnosis of long QT syndrome

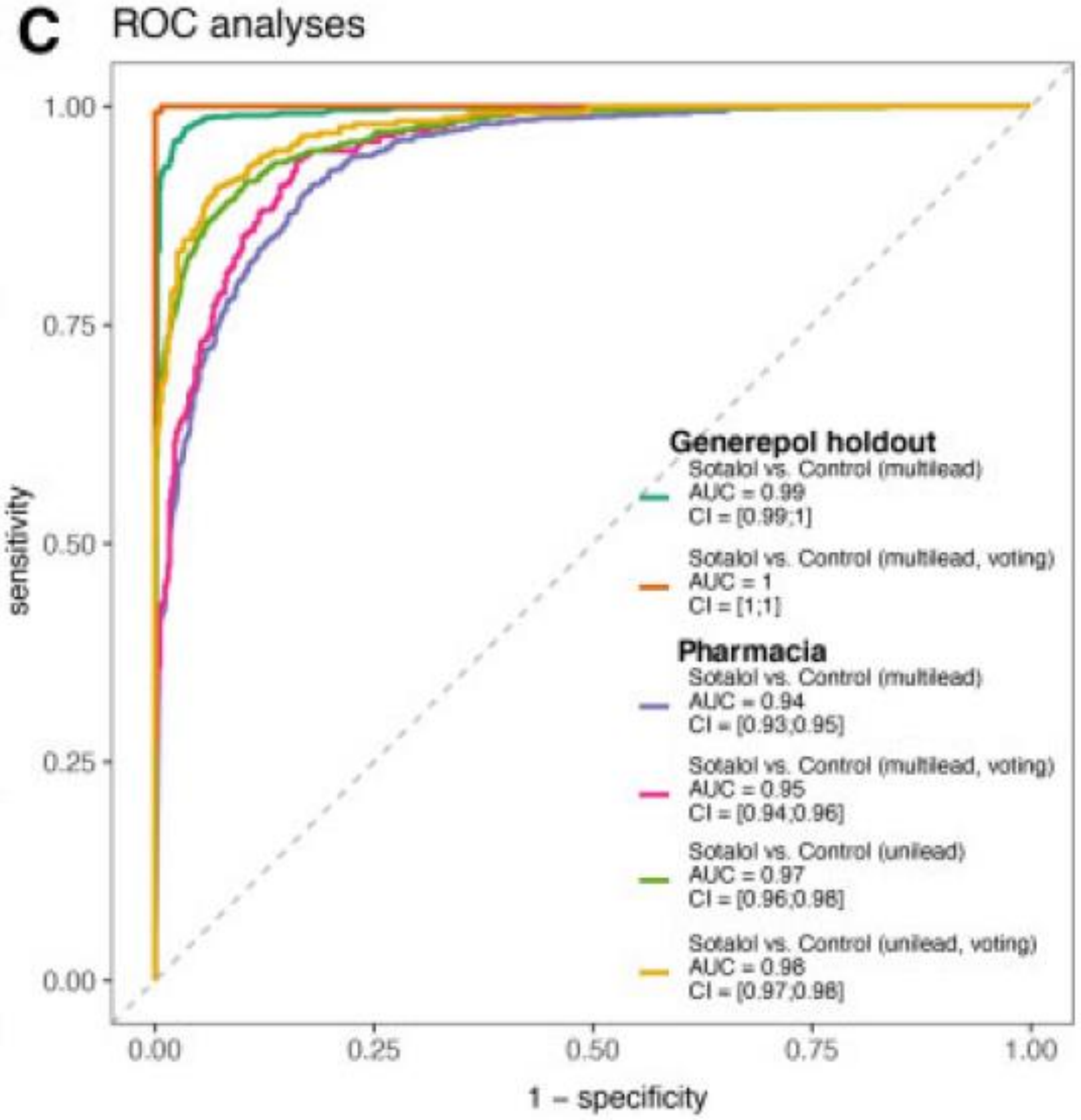
European Heart Journal. 2021;42:3948-61

Edi Prifti[1,2*], Ahmad Fall[1], Giovanni Davogustto[3†], Alfredo Pulini[1,4†], Isabelle Denjoy[5], Christian Funck-Brentano[6], Yasmin Khan[7], Alexandre Durand-Salmon[7], Fabio Badilini[8], Quinn S. Wells[3,9], Antoine Leenhardt[5], Jean-Daniel Zucker[1,2], Dan M. Roden[3,9,10], Fabrice Extramiana[5], and Joe-Elie Salem[3,6,9*]



QTcF alone
AUC of 0.695
(P< 1.5e-141 vs. CNN)

. p r a t i c o



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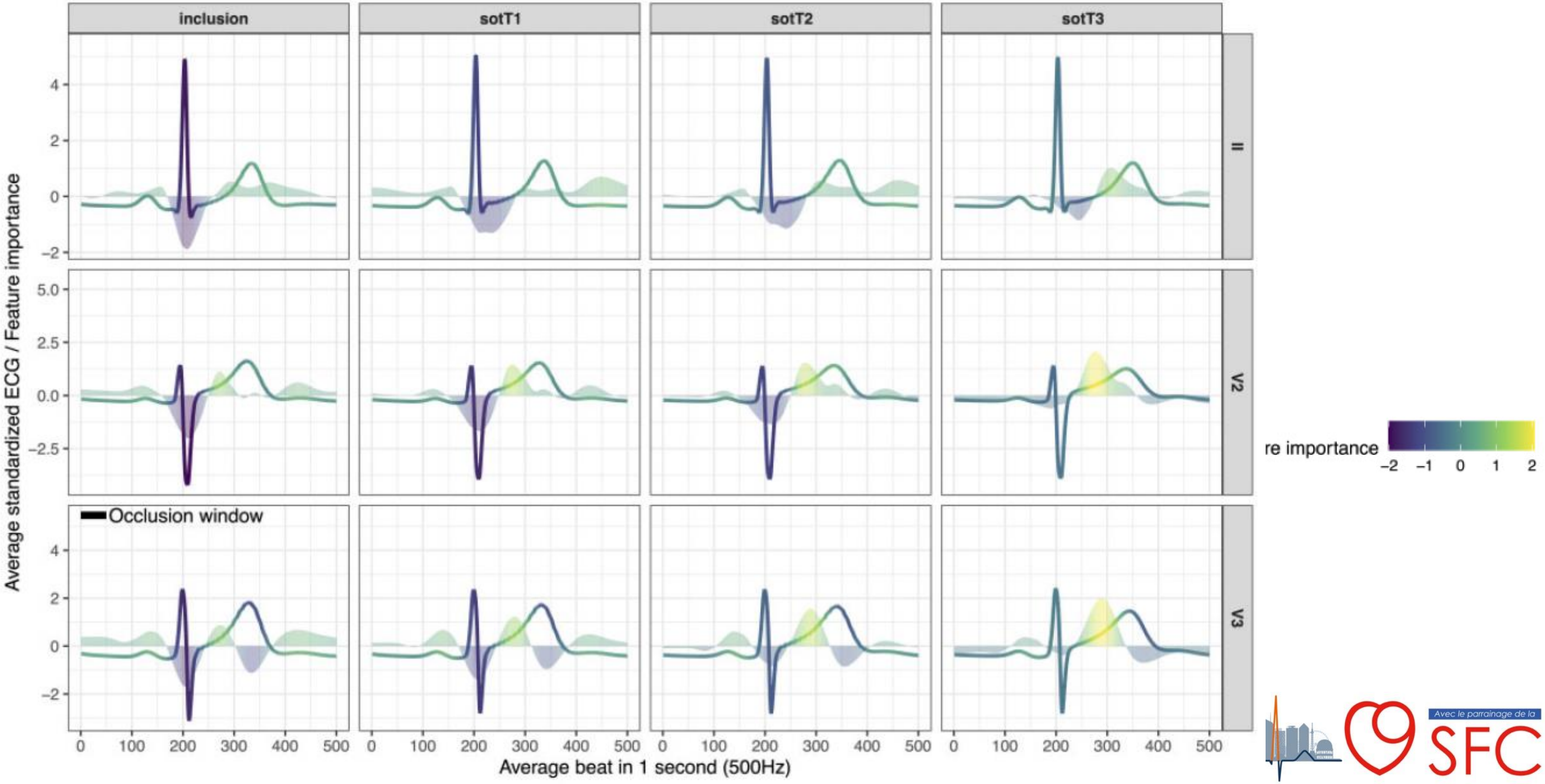


Collège National des Cardiologues des Hôpitaux

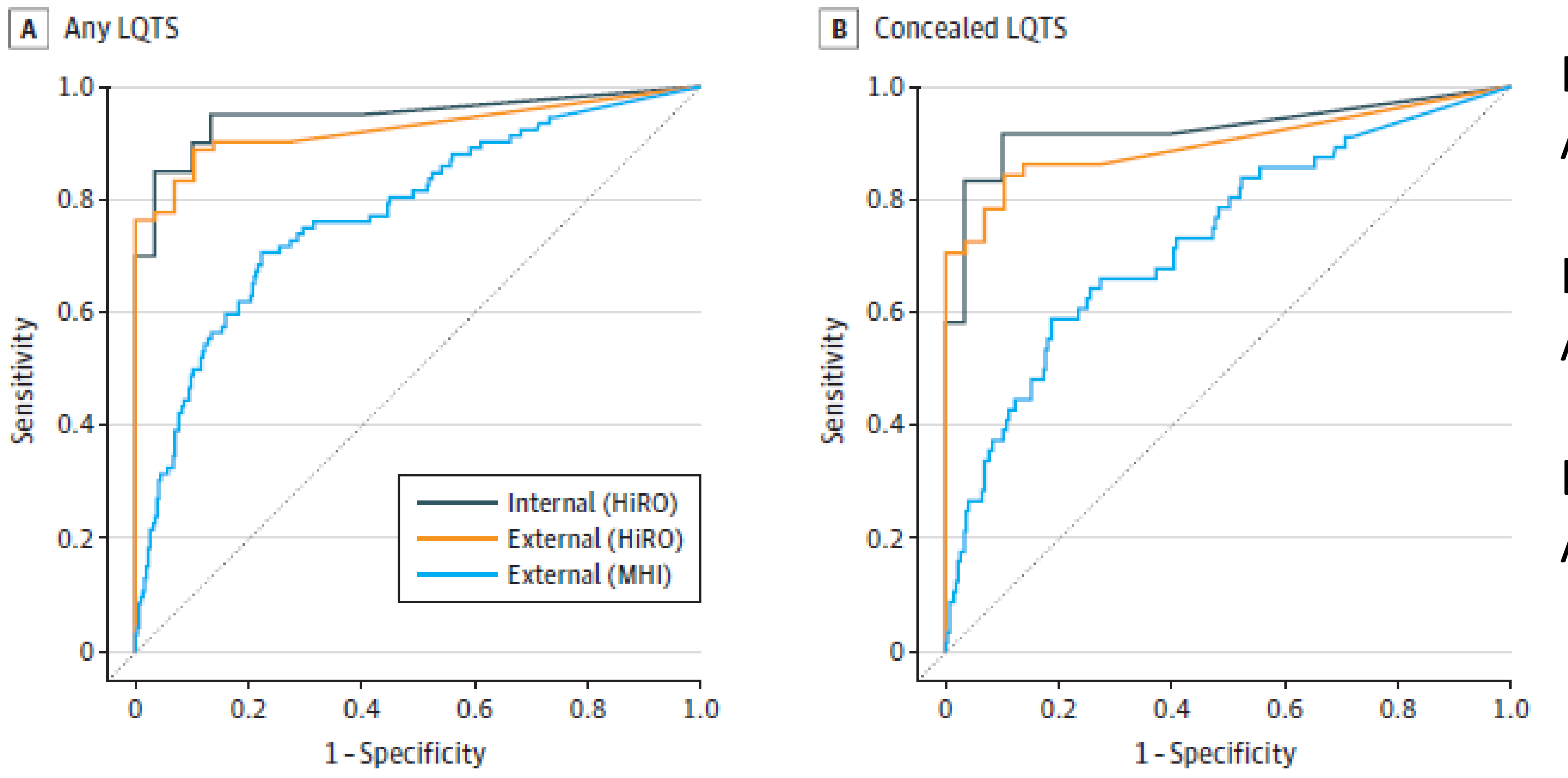
SFC
Avec le parrainage de la

Deep Learning–Augmented ECG Analysis for Screening and Genotype Prediction of Congenital Long QT Syndrome

River Jiang, MD; Christopher C. Cheung, MD, MPH; Marta Garcia-Montero, MD; Brianna Davies, MS; Jason Cao, BS;
Damian Redfearn, MD; Zachary M. Laksman, MD; Steffany Grondin, PhD; Joseph Atallah, MD;
Carolina A. Escudero, MD; Julia Cadrin-Tourigny, MD, PhD; Shubhayan Sanatani, MD; Christian Steinberg, MD;
Jacqueline Joza, MD; Robert Avram, MD; Rafik Tadros, MD, PhD; Andrew D. Krahn, MD

JAMA Cardiol. 2024; 9:377-384

Figure 3. Performance of a Deep Learning Model for Congenital Long QT Syndrome (LQTS) and Concealed LQTS Detection by Validation Subgroup



Internal model
AUC 0.95; 95%CI, 0.90-1.00

Internal validation
AUC 0.93; 95% CI, 0.89-0.96

External validation
AUC 0.78; 95% CI, 0.76-0.80

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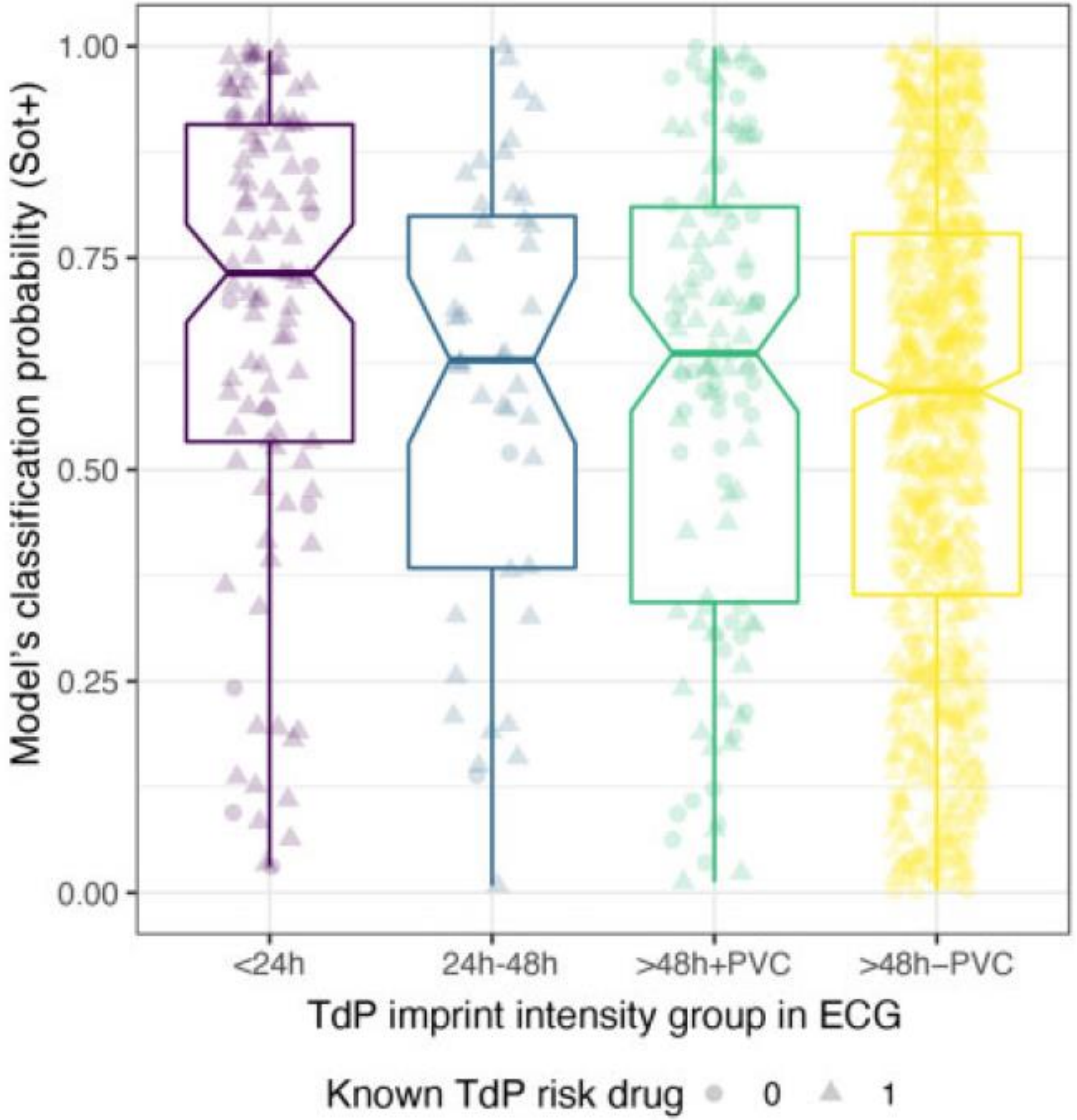
European Heart Journal. 2021;42:3948-61

Drug-induced TdP (diTdP)
Total (n=48; 1105 ECG)
24h (n=38; 103 ECG)
48h (n=31; 44 ECG)
>48h+PVC (n=28; 115 ECG)
>48h-PVC (n=48; 843 ECG)

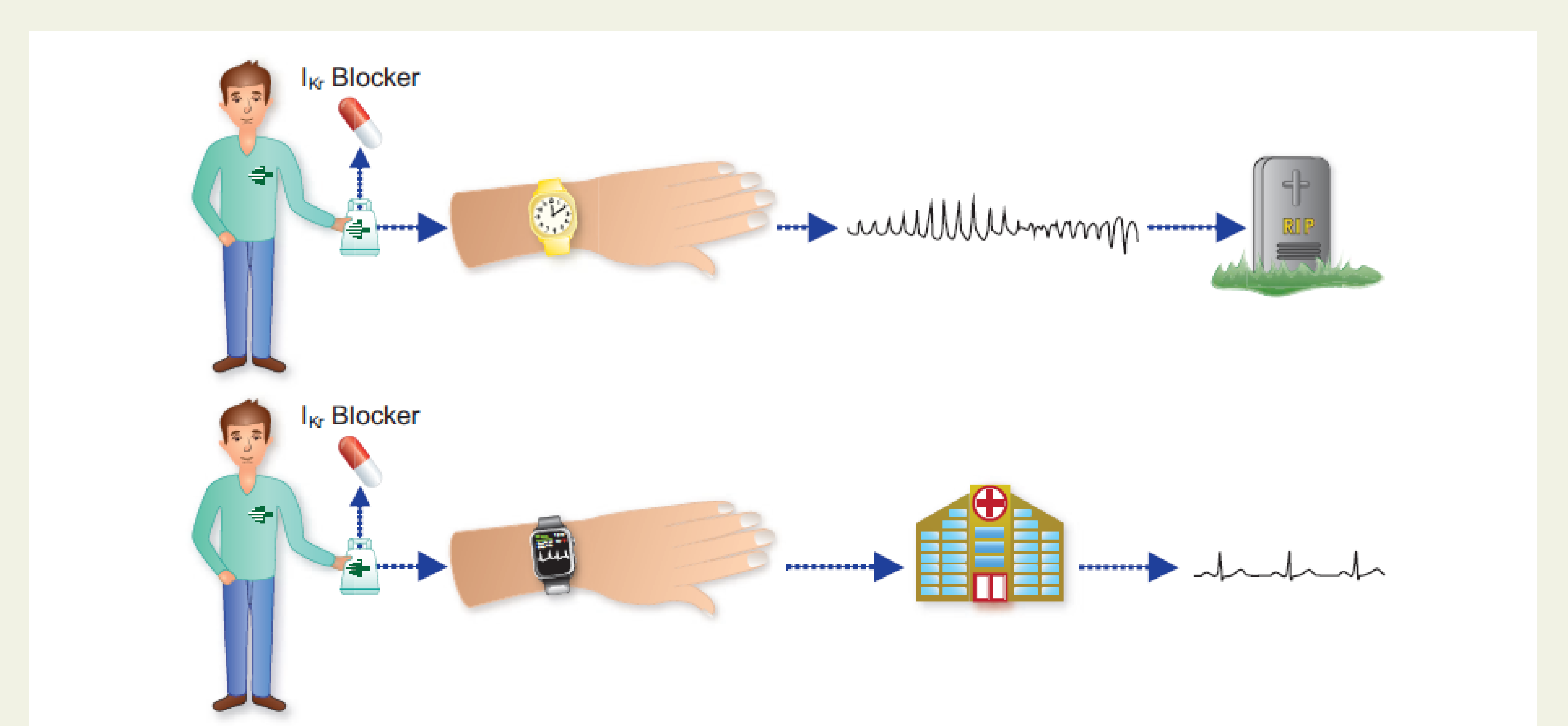


Long QT syndrome, artificial intelligence, and common sense

European Heart Journal 2021
doi:10.1093/eurheartj/ehab611

Peter J. Schwartz [1,2*] and Hanno L. Tan [3,4]

This editorial relates to 'Deep learning analysis of electrocardiogram for risk prediction of drug-induced arrhythmias and diagnosis of long QT syndrome' by E. Prifti *et al.*, doi:10.1093/eurheartj/ehab588.



ECG-Based Deep Learning and Clinical Risk Factors to Predict Atrial Fibrillation

Circulation. 2022; 145:122–133

Shaan Khurshid, MD, MPH*; Samuel Friedman, PhD*; Christopher Reeder, PhD; Paolo Di Achille, PhD; Nathaniel Diamant, BS; Pulkit Singh, BA; Lia X. Harrington, PhD; Xin Wang, MBBS, MPH; Mostafa A. Al-Alusi, MD; Gopal Sarma, MD, PhD; Andrea S. Foulkes, ScD; Patrick T. Ellinor, MD, PhD; Christopher D. Anderson, MD, MMSc; Jennifer E. Ho, MD; Anthony A. Philippakis, MD, PhD; Puneet Batra, PhD; Steven A. Lubitz, MD, MPH

Table 2. Model Performance for Incident Atrial Fibrillation in Test Sets

	MGH (n=4166)		BWH (n=37 963)		UK Biobank (n=41 033)	
Model	HR (per 1 SD)	5-year AUROC	HR (per 1 SD)	5-year AUROC	HR (per 1 SD)	2-year AUROC
Deep learning architectures						
ECG-AI	–	0.823* (0.790–0.856)	–	0.747* (0.736–0.759)	–	0.705 (0.659–0.724)
Cox proportional hazards models						
Age and sex	2.91 (2.44–3.47)	0.768 (0.732–0.805)	2.48 (2.35–2.62)	0.730 (0.717–0.743)	2.21 (1.96–2.50)	0.728 (0.702–0.755)
CHARGE-AF	3.36 (2.98–4.30)	0.802* (0.767–0.836)	2.78 (2.63–2.94)	0.752* (0.741–0.763)	2.26 (2.00–2.55)	0.732 (0.704–0.759)
ECG-AI	2.45 (2.23–2.69)	0.823* (0.790–0.856)	2.05 (1.98–2.11)	0.747* (0.736–0.759)	2.01 (1.88–2.14)	0.705 (0.673–0.737)
CH-AI	3.74 (3.24–4.33)	0.838*† (0.807–0.869)	2.76 (2.64–2.88)	0.777*† (0.766–0.788)	2.27 (2.11–2.44)	0.746 (0.716–0.776)

“universality” ?

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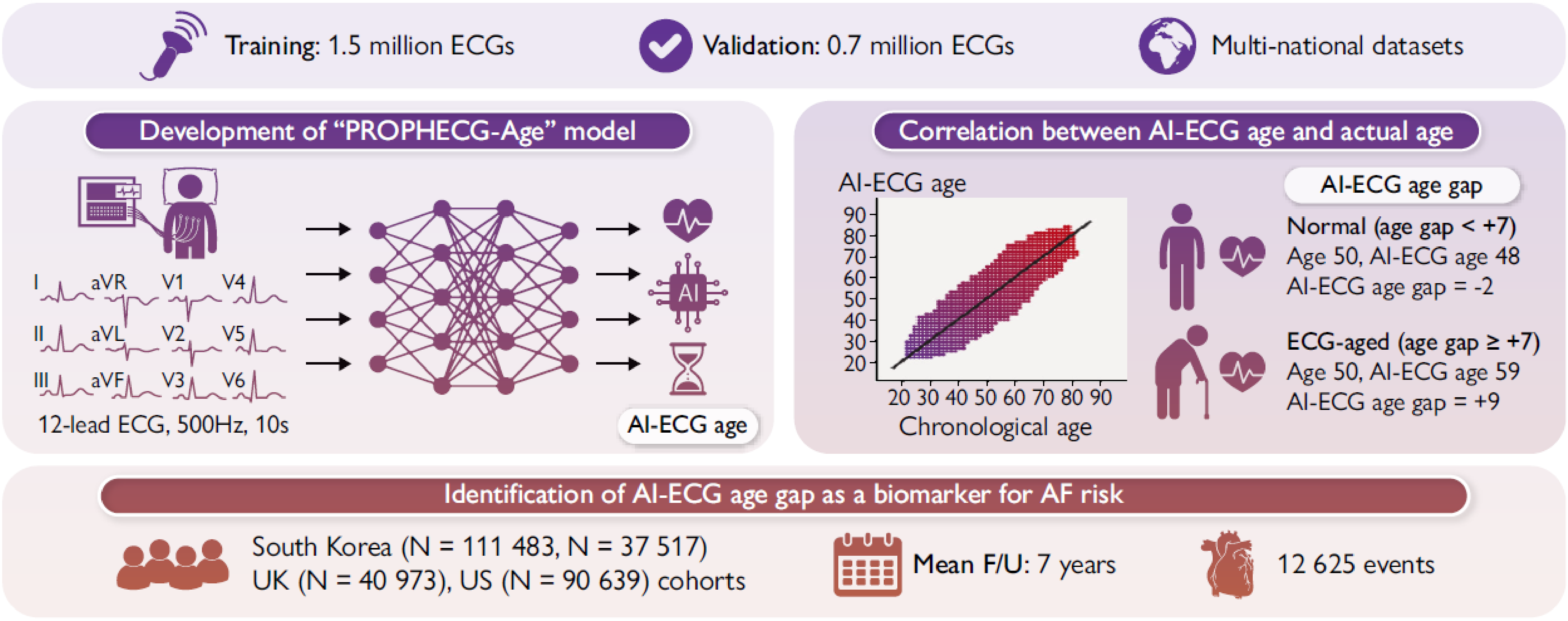
ECG-AI	–	0.823* (0.790–0.856)	–	0.747* (0.736–0.759)	–	0.705 (0.659–0.724)
Cox proportional hazards models						
Age and sex	2.91 (2.44–3.47)	0.768 (0.732–0.805)	2.48 (2.35–2.62)	0.730 (0.717–0.743)	2.21 (1.96–2.50)	0.728 (0.702–0.755)
CHARGE-AF	3.36 (2.98–4.30)	0.802* (0.767–0.836)	2.78 (2.63–2.94)	0.752* (0.741–0.763)	2.26 (2.00–2.55)	0.732 (0.704–0.759)
ECG-AI	2.45 (2.23–2.69)	0.823* (0.790–0.856)	2.05 (1.98–2.11)	0.747* (0.736–0.759)	2.01 (1.88–2.14)	0.705 (0.673–0.737)
CH-AI	3.74 (3.24–4.33)	0.838*† (0.807–0.869)	2.76 (2.64–2.88)	0.777*† (0.766–0.788)	2.27 (2.11–2.44)	0.746 (0.716–0.776)

Added value ?

Artificial intelligence–derived electrocardiographic aging and risk of atrial fibrillation: a multi-national study

Eur Heart J. 2025; 46:839-852

Seunghoon Cho [1†], Sujeong Eom [2,3†], Daehoon Kim [1], Tae-Hoon Kim [1], Jae-Sun Uhm [1], Hui-Nam Pak [1], Moon-Hyoung Lee [1], Pil-Sung Yang [4], Eunjung Lee [5], Zachi Itzhak Attia [5], Paul Andrew Friedman [5], Seng Chan You [2,3,*], Hee Tae Yu [1,*], and Boyoung Joung [1,*]



Artificial intelligence–derived electrocardiographic aging and risk of atrial fibrillation: a multi-national study

Seunghoon Cho [1†], Sujeong Eom [2,3†], Daehoon Kim [1], Tae-Hoon Kim [1], Jae-Sun Uhm [1], Hui-Nam Pak [1], Moon-Hyoung Lee [1], Pil-Sung Yang [4], Eunjung Lee [5], Zachi Itzhak Attia [5], Paul Andrew Friedman [5], Seng Chan You [2,3,*], Hee Tae Yu [1,*], and Boyoung Joung [1,*]

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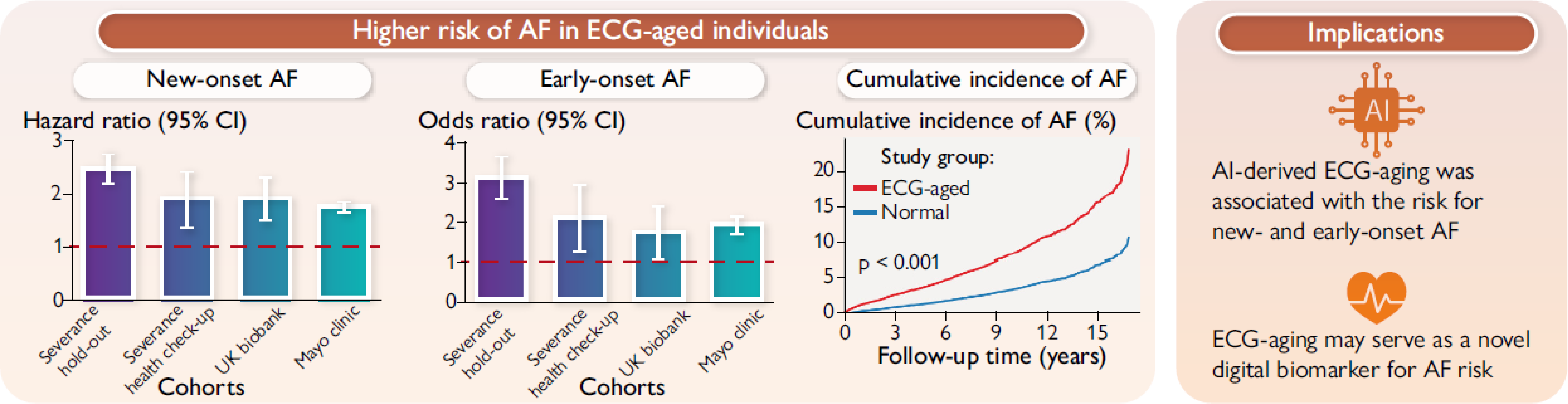


Artificial Intelligence–Enhanced Electrocardiography for Complete Heart Block Risk Stratification

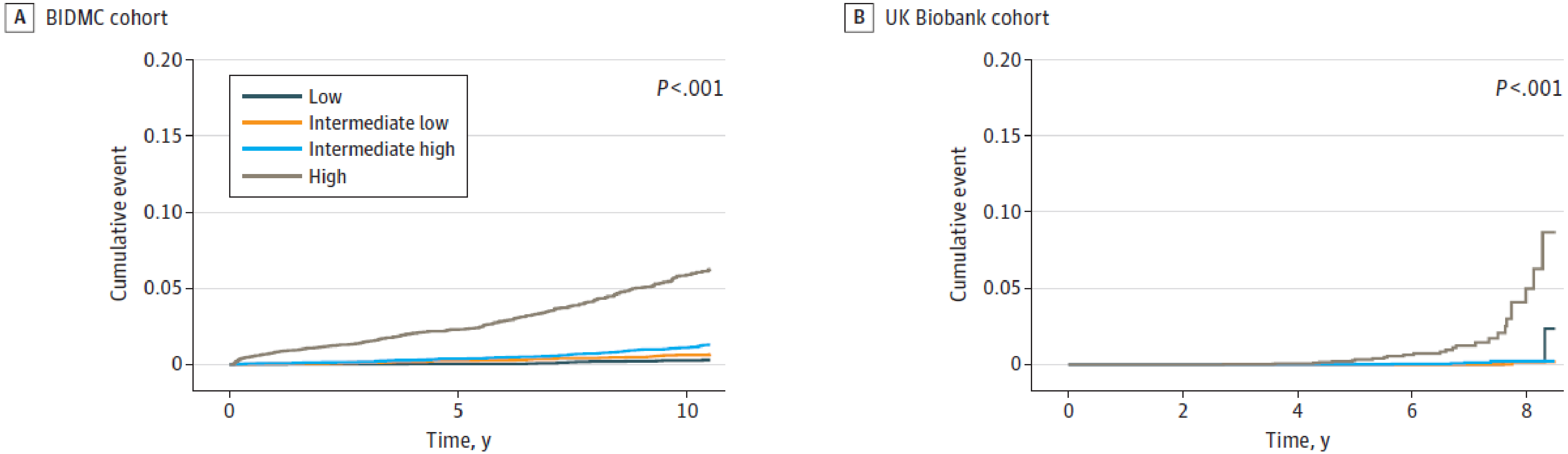
Arunashis Sau, PhD; Henry Zhang, BSc; Joseph Barker, MRes; Libor Pastika, MBBS; Konstantinos Patlatzoglou, PhD; Boroumand Zeidaabadi, BSc; Ahmed El-Medany, MBBS; Gul Rukh Khattak, PhD; Kathryn A. McGurk, PhD; Ewa Sieliwonczyk, PhD; James S. Ware, PhD; Nicholas S. Peters, MD; Daniel B. Kramer, MD; Jonathan W. Waks, MD; Fu Siong Ng, PhD

JAMA Cardiol. 2025;
doi:10.1001/jamacardio.2025.2522

163 401 ECGs from
189 539 patients

- C index of 0.836 (95%CI, 0.819-0.534)
- AUROC 0.889 (95%CI, 0.863-0.916)

Figure 1. Artificial Intelligence–Enhanced Electrocardiography Risk Estimator for Complete Heart Block (AIRE-CHB) Prediction of Incident CHB



A No. at risk

	0	5	10
Low	15231	7441	3611
Intermediate low	15559	8652	4609
Intermediate high	15201	8085	4184
High	15685	6541	2901

B No. at risk

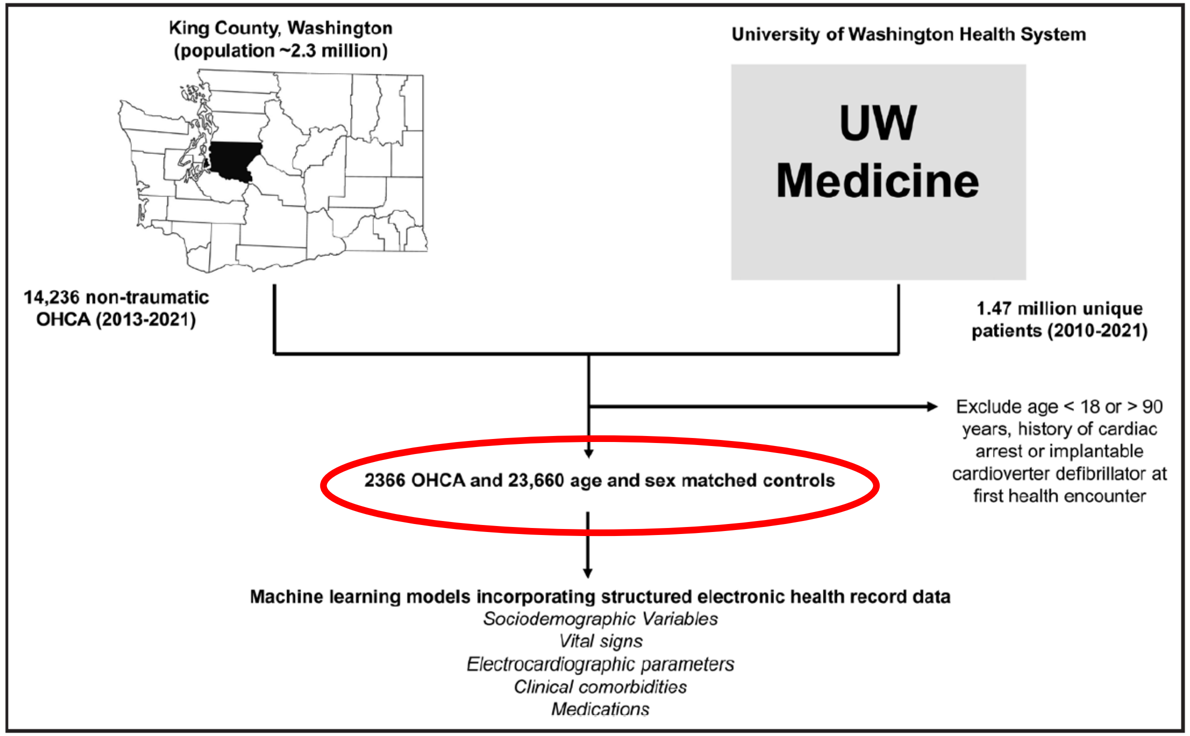
	0	2	4	6	8
Low	10264	8570	5223	1954	189
Intermediate low	16782	13713	8449	3385	254
Intermediate high	16632	13374	8232	3374	227
High	6963	5650	3322	1076	102

AIRE-CHB stratified risk of incident CHB in the Beth Israel Deaconess Medical Center (BIDMC) (A) and UK Biobank (B) cohorts. Kaplan-Meier curves show cumulative probabilities of complete heart block for the 4 quartiles of risk defined by AIRE-CHB predictions using a single ECG.

Predicting Out-of-Hospital Cardiac Arrest in the General Population Using Electronic Health Records

Circulation. 2024;149:
DOI: 10.1161

Jessica Perry, MSc; Jennifer A. Brody, BA; Christine Fong, MSc; Jacob E. Sunshine, MD;
Vikas N. O'Reilly-Shah, MD, PhD; Michael R. Sayre, MD; Thomas D. Rea, MD, MPH; Noah Simon, PhD; Ali Shojaie, PhD;
Nona Sotoodehnia, MD; Neal A. Chatterjee, MD, MSc



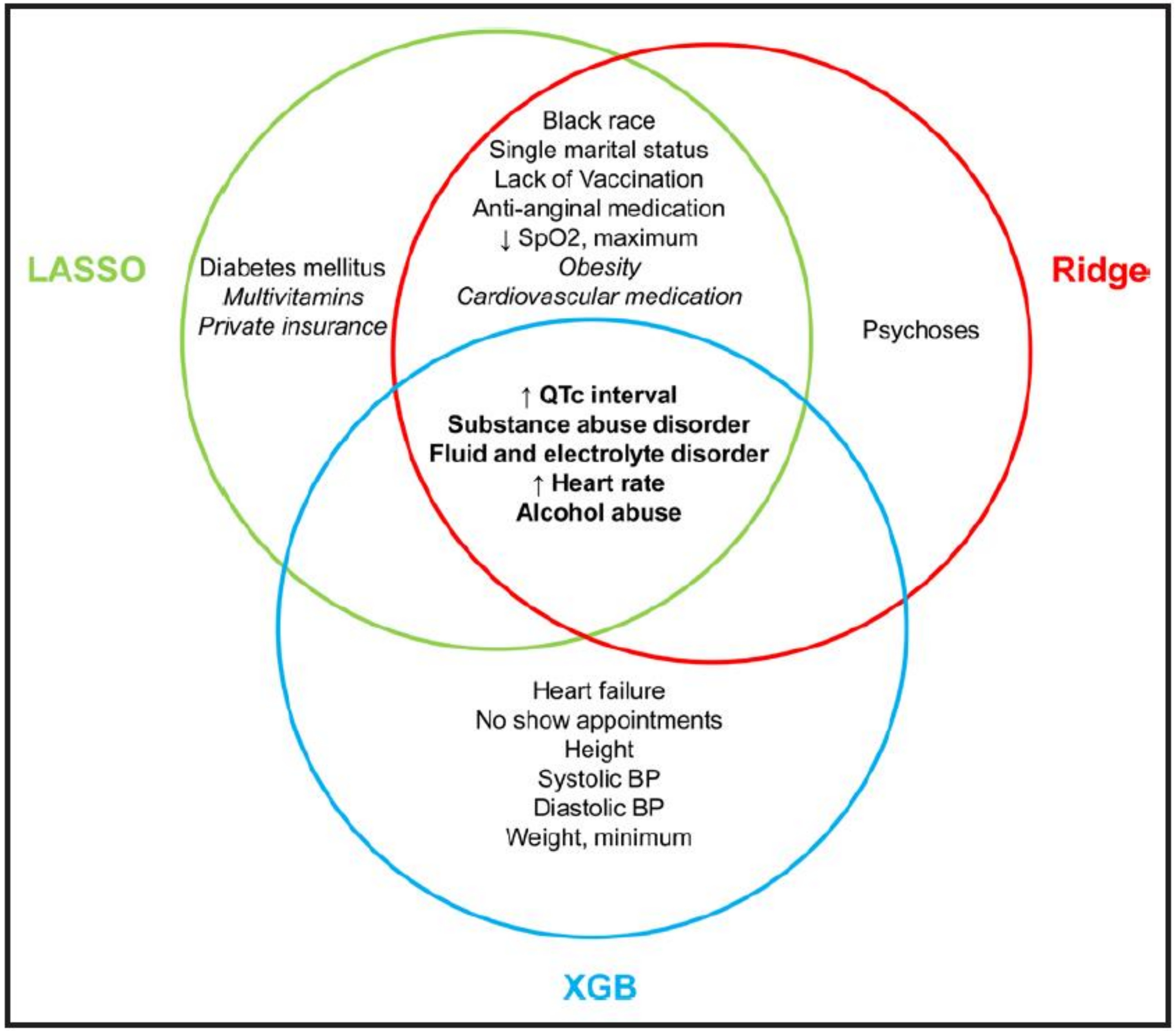


Figure 3. Covariate importance consensus among machine learning models predicting out-of-hospital cardiac arrest.

Predicting Out-of-Hospital Cardiac Arrest in the General Population Using Electronic Health Records

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Table 2. Model Performance for Prediction of Out-of-Hospital Cardiac Arrest

Variable	Internal validation (n=18218)				External validation (n=7808)			
	Baseline	Ridge	Lasso	XGBoost	Baseline	Ridge	Lasso	XGBoost
AUC (95% CI)	0.68 (0.66–0.69)	0.82 (0.81–0.83)	0.82 (0.81–0.83)	0.95 (0.94–0.95)	0.66 (0.64–0.68)	0.80 (0.79–0.82)	0.81 (0.79–0.82)	0.85 (0.84–0.87)
Sensitivity*	0.04	0.15	0.15	0.51	0.04	0.14	0.14	0.18
PR-AUC	0.18	0.40	0.39	0.75	0.18	0.36	0.36	0.42
PR-AUC, adjusted†	0.004	0.02	0.02	0.31	0.004	0.02	0.02	0.02
PPV*	0.27	0.61	0.60	0.84	0.31	0.58	0.59	0.64
PPV, adjusted†	0.007	0.027	0.027	0.084	0.008	0.025	0.026	0.031
NPV*	0.91	0.92	0.92	0.95	0.91	0.92	0.92	0.92
NPV, adjusted†	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99

†Denoted model measures are sensitive to underlying disease incidence. Adjustment reflects estimated performance when deployed across the entire University of Washington health system

Near-term prediction of sustained ventricular arrhythmias applying artificial intelligence to single-lead ambulatory electrocardiogram

European Heart Journal
2025;46:1998–2008

Laurent Fiorina [1,2,†], Tanner Carbonati[3,†], Kumar Narayanan [2,4], Jia Li[3], Christine Henry[3], Jagmeet P. Singh[5], and Eloi Marijon [2,6,*]

Table 2 Internal and external validation performance by subgroups

	n	*n* VT	AUROC (95% CI)	AUPRC (95% CI)	Sens. (95% CI)	Spe. (95% CI)	PPV (95% CI)	NPV (95% CI)
Internal validation								
Age								
18–65	20 789	97	97.1 (95.3–98.6)	44.0 (34.0–54.8)	74.2 (64.8–82.5)	98.6 (98.4–98.7)	19.4 (15.3–23.3)	99.9 (99.8–99.9)
≥65	22 988	100	94.2 (91.7–96.3)	18.1 (12.7–27.4)	67.0 (57.3–75.8)	97.0 (96.8–97.2)	8.9 (7.0–11.0)	99.9 (99.8–99.9)
Sex								
Male	16 836	143	95.0 (93.4–96.4)	32.7 (25.3–41.2)	71.3 (63.6–78.5)	96.1 (95.8–96.4)	13.6 (11.4–16.2)	99.7 (99.7–99.8)
Female	26 941	54	94.6 (90.8–97.8)	26.2 (15.3–39.0)	68.5 (55.3–80.9)	98.7 (98.6–98.9)	9.8 (7.0–13.1)	99.9 (99.9–100.0)
External validation								
Age								
18–65	10 634	41	95.1 (91.6–98.2)	33.1 (19.7–48.0)	63.4 (48.6–77.6)	98.8 (98.5–99.0)	16.5 (10.9–22.3)	99.9 (99.8–99.9)
≥65	9966	62	94.0 (91.4–96.2)	24.3 (14.7–37.0)	45.2 (32.3–57.6)	97.8 (97.5–98.1)	11.6 (7.8–15.8)	99.7 (99.5–99.8)
Sex								
Male	8517	82	93.2 (90.7–95.5)	28.8 (19.5–39.4)	50.0 (39.4–60.5)	97.2 (96.8–97.5)	14.7 (10.7–19.2)	99.5 (99.3–99.7)
Female	12 083	21	94.5 (88.4–99.1)	20.9 (9.6–41.3)	61.9 (40.0–81.2)	99.1 (98.9–99.3)	10.7 (5.2–16.7)	99.9 (99.9–100.0)

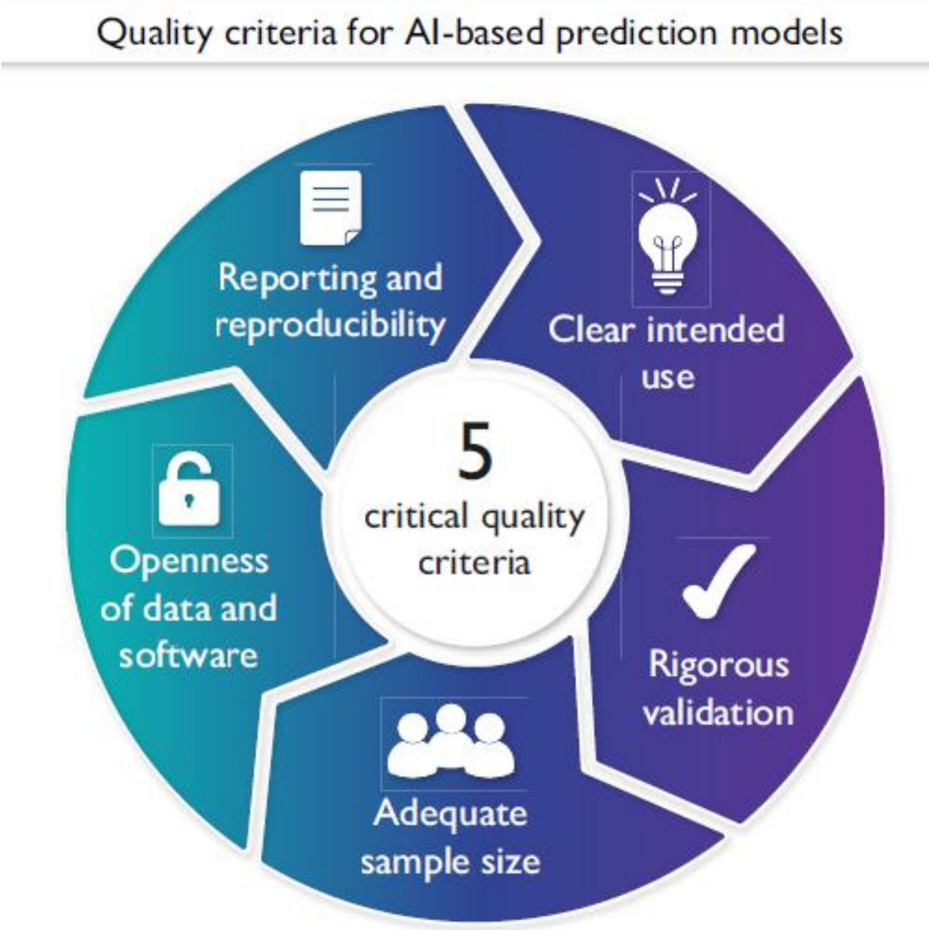
Apport de l'IA en Rythmologie en 2025 :
vraiment pertinente cliniquement au lit du patient ?

Performance / Pertinence

- Quelles métriques (Sens/Spe/VPP/VPN/Accuracy/F1-score/AUC…) ?
- Quels comparateurs ?
- Quelle « généralisabilité » ?
- Quelle explicabilité ?
- Quelles utilisations actuelles ?
- Quels risques ?

Five critical quality criteria for artificial intelligence-based prediction models

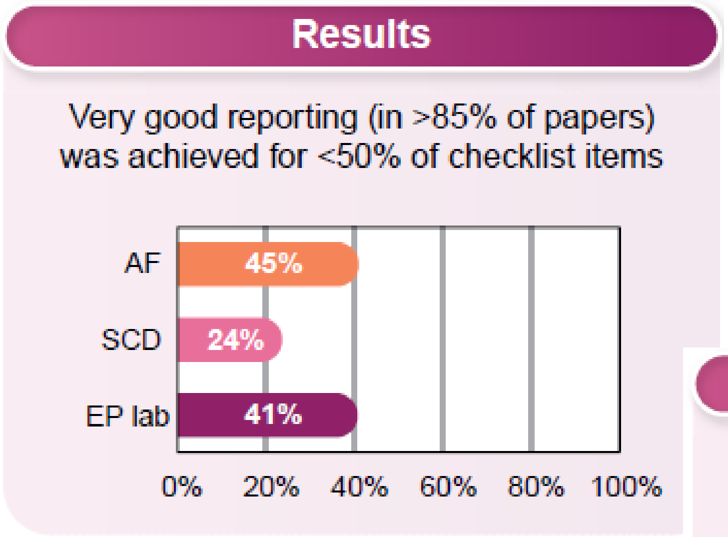
Florien S. van Royen[1], Folkert W. Asselbergs[2,3], Fernando Alfonso[4], Panos Vardas[5], and Maarten van Smeden[6,7]*

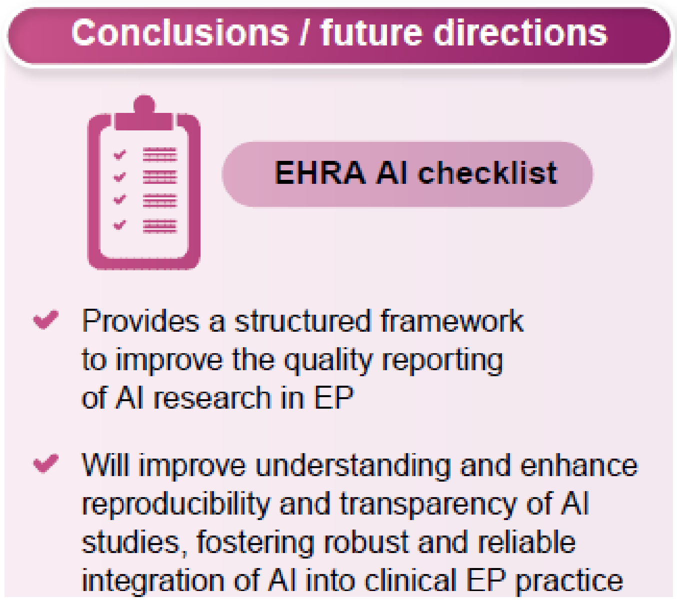


European Heart Journal
2023.44:4831–4834

ESC European Society of Cardiology
Europace (2025) 27, euaf071
https://doi.org/10.1093/europace/euaf071
EHRA DOCUMENT
EHRA European Heart Rhythm Association

State of the Art of Artificial Intelligence in Clinical Electrophysiology in 2025: A Scientific Statement of the European Heart Rhythm Association (EHRA) of the ESC, the Heart Rhythm Society (HRS), and the ESC Working Group on E-Cardiology





nature > news > article

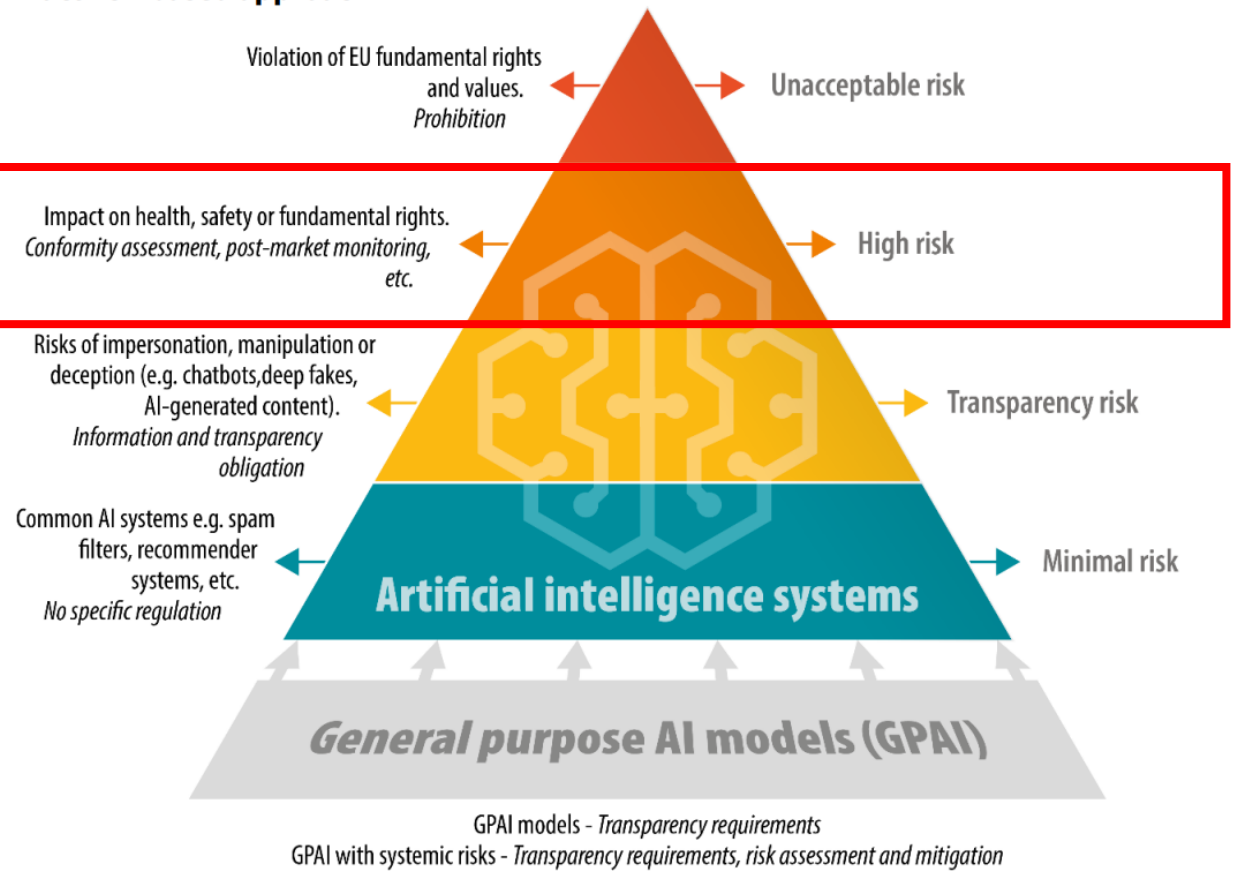
NEWS | 27 November 2025

Major AI conference flooded with peer reviews written fully by AI

Controversy has erupted after 21% of manuscript reviews for an international AI conference were found to be generated by artificial intelligence.

Artificial intelligence act (europa.eu)

EU AI act risk-based approach



Data source: European Commission

Potential risk associated with AI

- Unreliable data & results
- Medical responsibility issues
- Loss of medical privacy
- Distortion of data for future studies
- Loss of expertise
- …

- Energy supply / carbon footprint
- Data & software private concentration
- Financial bubble
- …

Glossaire statistique

Validité intrinsèque d'un test

Sensibilité mesure la capacité d'un test à donner un résultat positif lorsqu'une hypothèse est vérifiée

Spécificité mesure la capacité d'un test à donner un résultat négatif lorsque l'hypothèse n'est pas vérifiée

Valeur prédictive, ou valeur diagnostique

La valeur prédictive positive * est la probabilité que la maladie soit présente lorsque le test est positif

La valeur prédictive négative * est la probabilité que la maladie ne soit pas présente lorsque le test est négatif

AUC / AUROC * est l'aire sous la courbe de la fonction d'efficacité du récepteur (courbe ROC = Receiver Operating Characteristic)

= taux de vrais positifs en fonction du taux de faux positifs

L'exactitude est la proportion de prédictions correctes (à la fois vraies positives et vraies négatives) parmi le nombre total de cas examinés,

Elle se décompose en : **justesse** et **fidélité** de mesure

Le rappel (recall) est le pourcentage de positifs bien prédit par le modèle

La précision est le nombre de prédictions positifs bien effectuées

Le score F1 ** combine les mesures de précision et rappel (basées sur les taux de vrais positifs, faux positifs et faux négatifs

$$F_1 = 2 \cdot \frac{(\text{précision} \cdot \text{rappel})}{(\text{précision} + \text{rappel})} = \frac{2VP}{2VP + FP + FN}$$

* dépend de la distribution des classes

** ne tient pas compte du taux de vrais négatifs → F-mesure inadaptée aux problèmes de classification où les vrais négatifs seraient importants (par exemple le diagnostic médical)

FUTURE AI

HOME FUTURE-AI GUIDELINES ▾ ASSESSMENT CHECKLIST CURRENT PROJECTS ▾ CONSORTIUM CONTACT US

FUTURE-AI: Best practices for trustworthy AI in medicine

FUTURE-AI is an international, multi-stakeholder initiative for defining and maintaining concrete guidelines that will facilitate the design, development, validation and deployment of trustworthy AI solutions in medicine and healthcare based on six guiding principles: Fairness, Universality, Traceability, Usability, Robustness and Explainability.

1

Fairness

The first principle of the FUTURE-AI guidelines is the one of Fairness, which states that medical AI algorithms should maintain...

Learn More ▸

2

Universality

While a certain degree of diversity in the design and implementation of AI solutions in medicine is both expected and desirable...

Learn More ▸

3

Traceability

The traceability principle states that medical AI algorithms should be developed together with mechanisms for documenting and m...

Learn More ▸

4

Usability

The Usability principle states that the medical AI solutions should be usable, acceptable and deployable for the end-users in r...

Learn More ▸

5

Robustness

The Robustness principle refers to the ability of a medical AI model to maintain its performance and accuracy when it is applie...

Learn More ▸

6

Explainability

The sixth and final principle of the FUTURE-AI guidelines is the one of Explainability, which states that medical AI algorithms...

Learn More ▸

Is your medical AI technology FUTURE-AI ready?

The FUTURE-AI assessment checklist consists of concrete and actionable questions that will guide developers, evaluators and other stakeholders in delivering medical AI tools that are trustworthy and optimised for real-world practice.

CHECKLIST

54 items

Nature 2025;642:864

Comment

Clinical trials for breast-cancer screening are under way using imaging devices assisted by artificial intelligence.

Why predictive modelling in health care is a house of cards

Akhil Vaid

The uncontrolled deployment of machine learning in medicine can distort patient information and sacrifice long-term data reliability for short-term benefits.

The practice of modern medicine is built on pattern recognition — whether in a patient's history, physical examination, laboratory results or response to treatment. A skilled physician can identify crucial patterns early and distinguish them from others that appear deceptively similar.

But some patterns are too chaotic, too subtle or too fleeting to raise red flags. No doctor can reliably catch early-stage pancreatic cancer from routine blood tests, for example. Answers to many questions of profound importance that demand knowledge of the future[1], such as whether a tumour will spread or how long a person might live, are thus subjective — often coming down to a physician's cumulative experience or 'gut feeling'.

One approach to reducing subjectivity in medicine is through supervised machine learning — a technique based on creating computer models that can detect patterns by learning from labelled data. For instance,

Educational Strategies for Clinical Supervision of Artificial Intelligence Use

N Engl J Med 2025; 393:786-97

Raja-Elie E. Abdulnour, M.D.,[1] Brian Gin, M.D., Ph.D.,[2] and Christy K. Boscardin, Ph.D.[3,4]

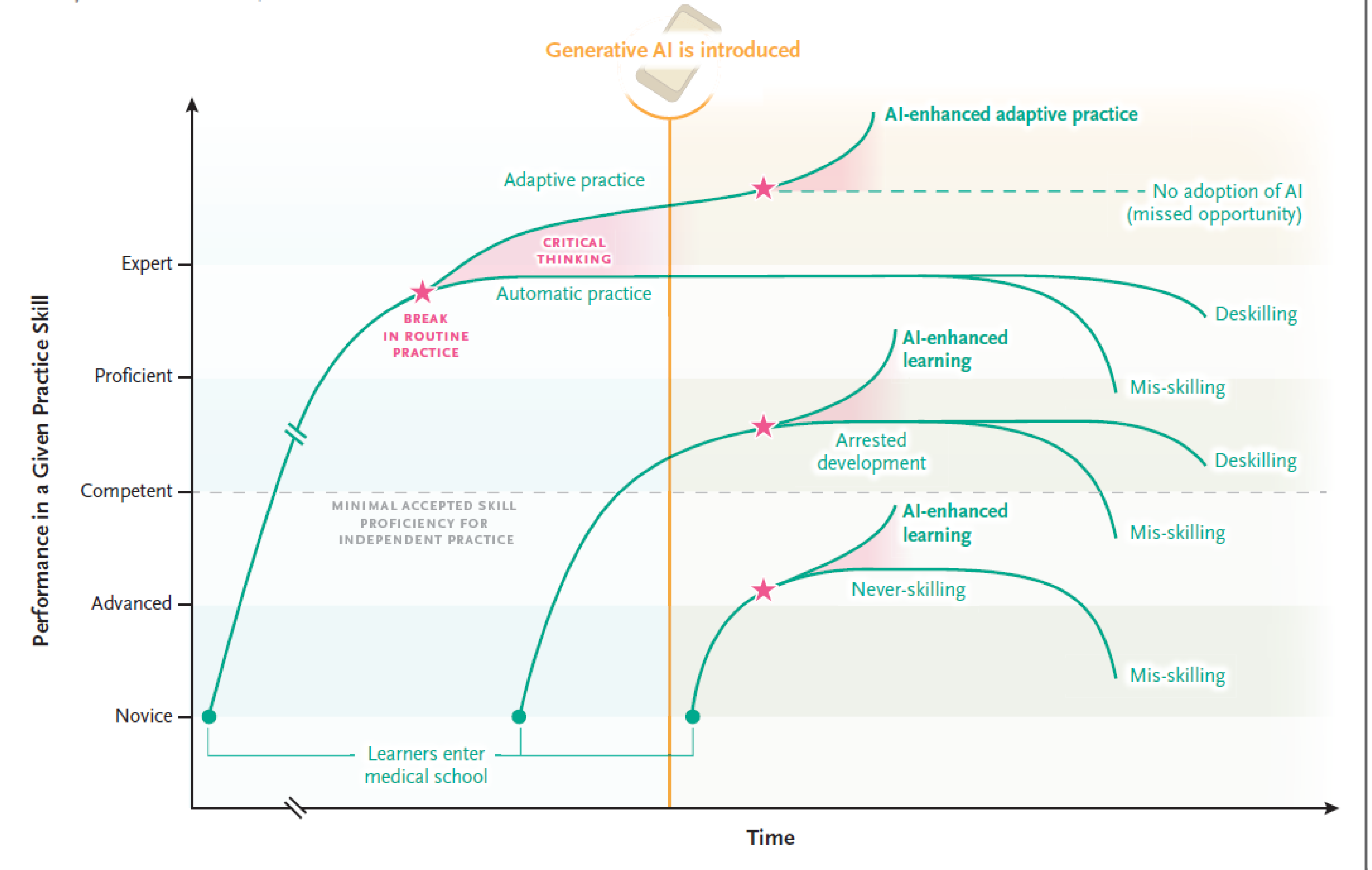


Figure 2. **Development of Adaptive Practice and the Effects of AI.**