

IA, ECG et prédiction de la MSC

Etat des lieux

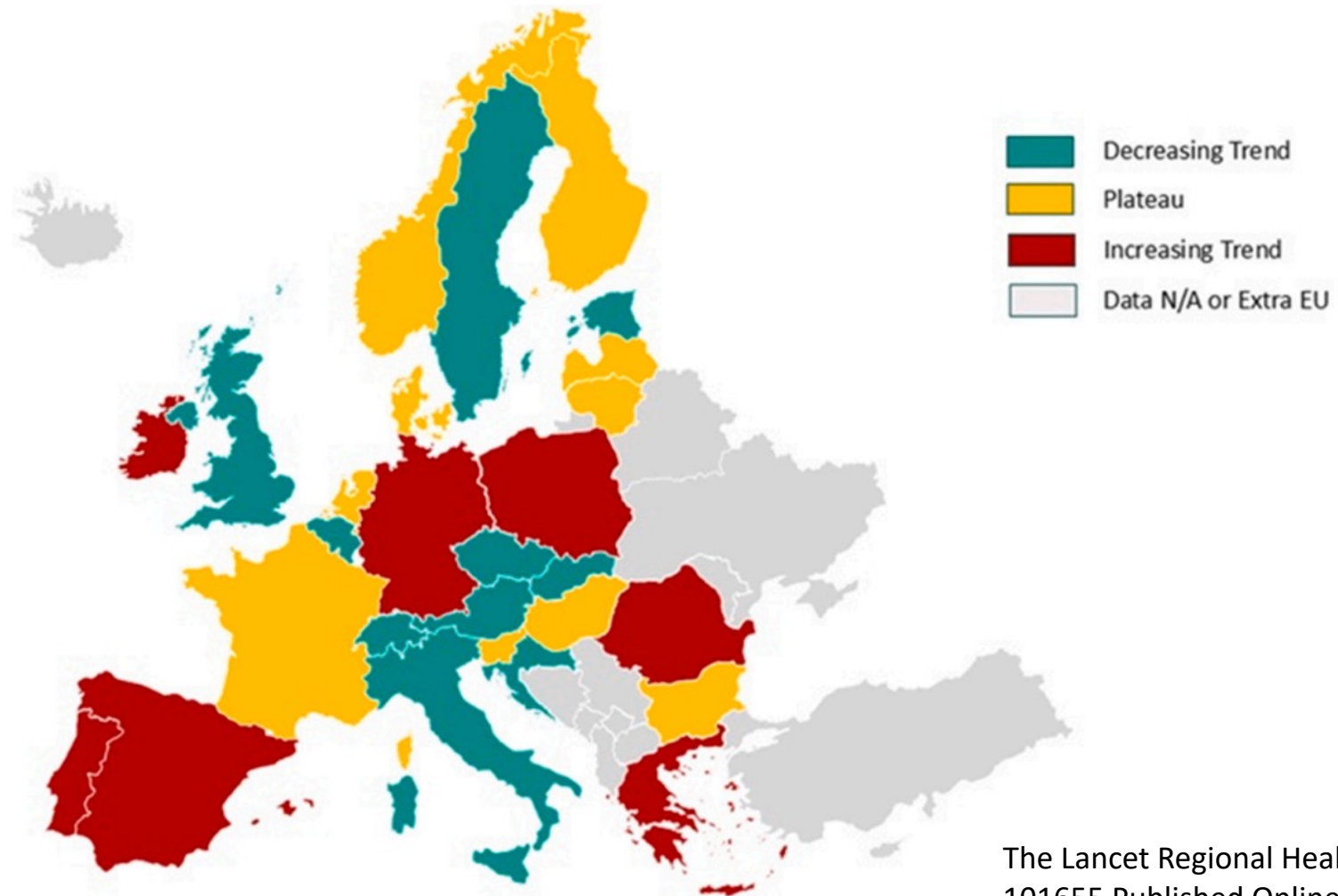
Pr Gabriel LAURENT

Service de cardiologie, CHU Dijon

Données récentes

- MSC en Europe
- IA dans la littérature depuis 25 ans pour la prédiction de la MSC
- IA et ECG:
 - Au-delà de la FE
 - L'ECG en plus des critères cliniques habituels de prédiction
 - Modifications de l'ECG dans le temps
 - QT et dyskaliémie
 - Le Holter
 - Au-delà de l'ECG

Mort subite: tendances en Europe de 2012 à 2021



The Lancet Regional Health - Europe 2026;66:
101655 Published Online 23 April 2026



ECG, sudden cardiac death prediction, artificial intelligence



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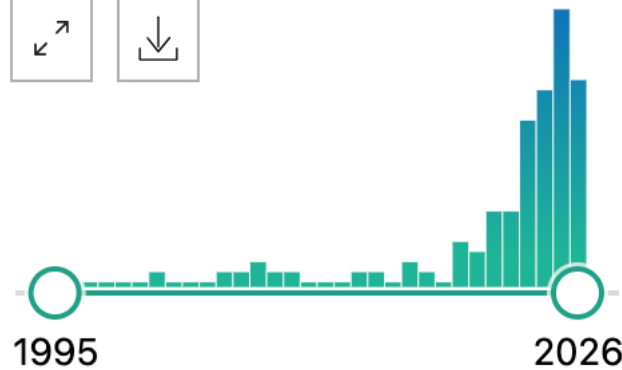
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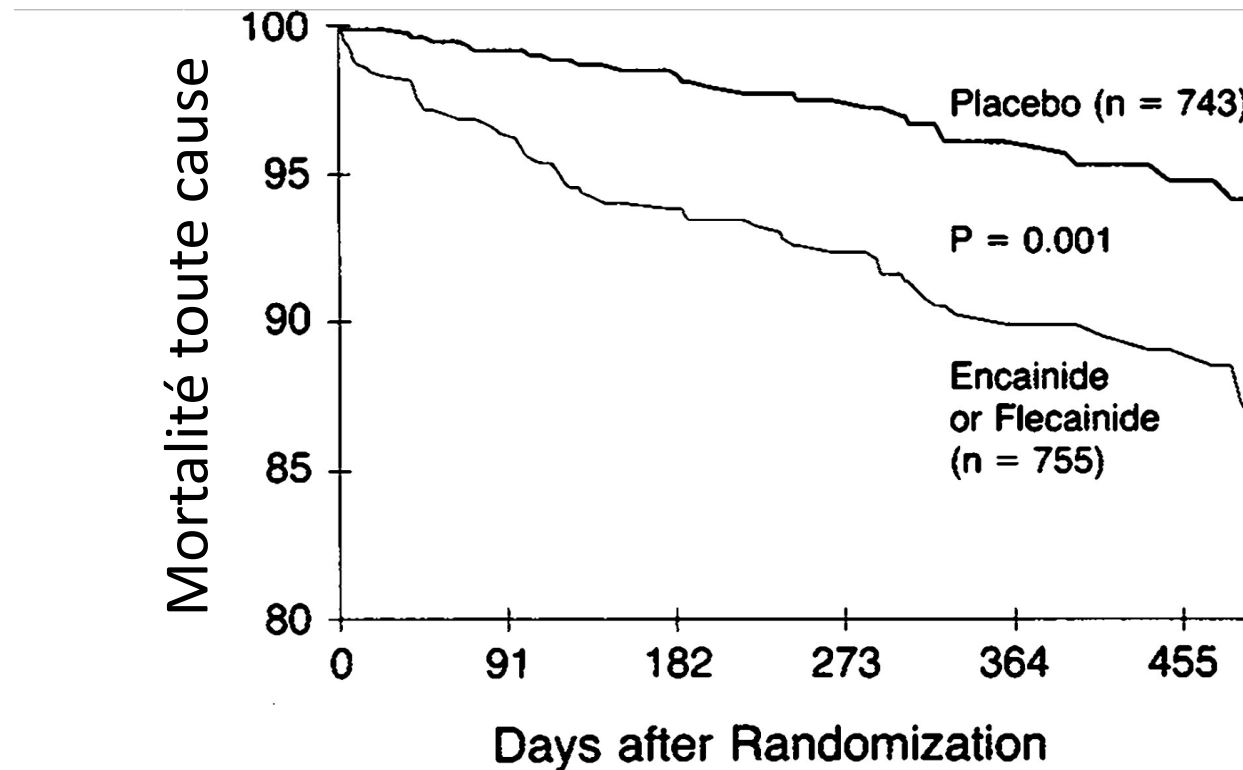
Noninvasive prediction of sudden death and sustained ventricular tachycardia after acute myocardial infarction using a neural network algorithm

En post IDM il est possible de prédire le risque de mort subite rythmique à partir des paramètres suivants: **IC à la phase aigüe, dyskinésie ventriculaire, potentiels tardifs, nombre d'ESV/24h, TVNS, FEVG basse musique, BBG, traitement digitalique à la sortie.**

« Les patients à risque sont candidats à un traitement anti-arythmique préventif ».

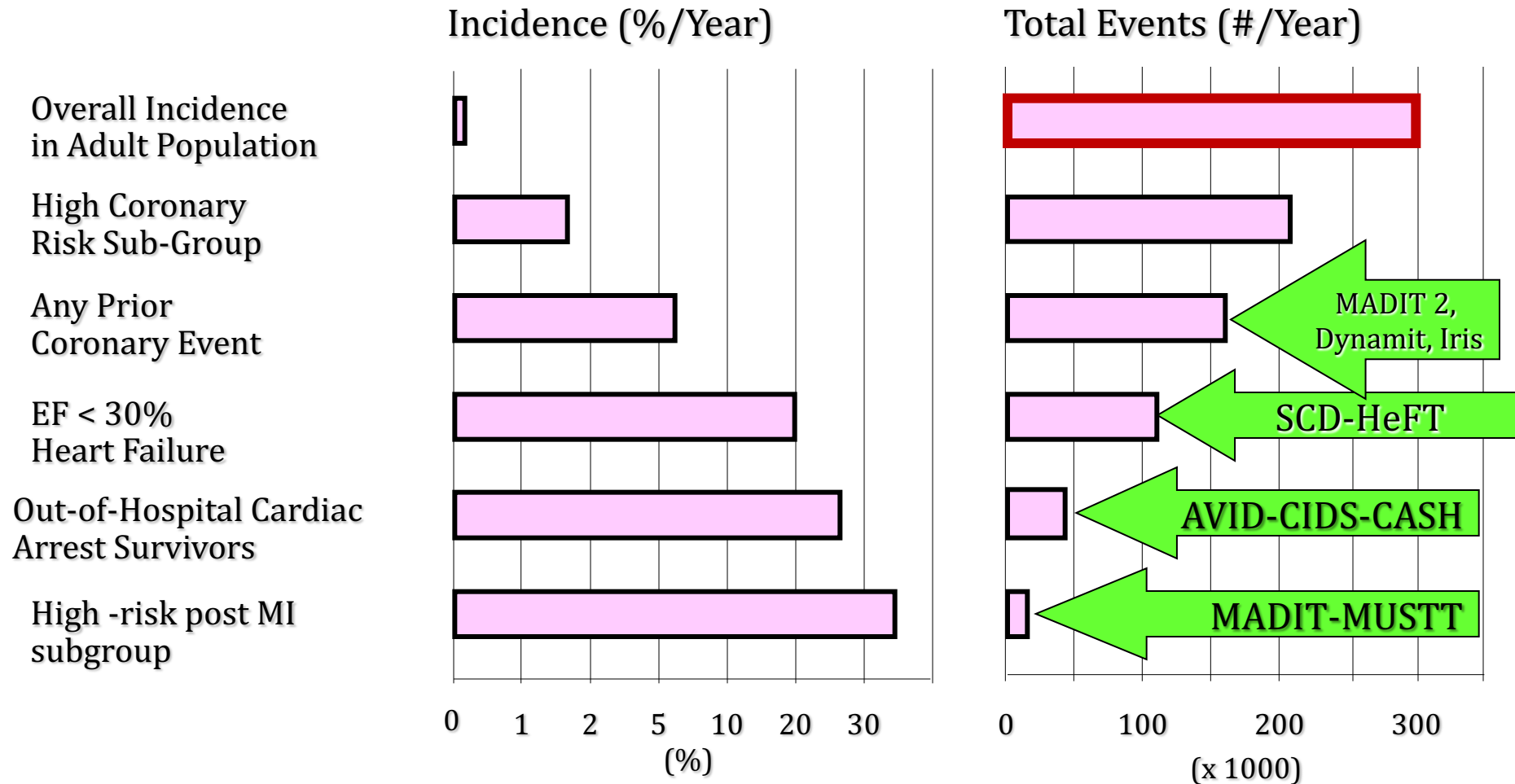
Etude CAST

Mortality and Morbidity in Patients Receiving Encainide, Flecainide, or Placebo — The Cardiac Arrhythmia Suppression Trial



Placebo	743	625	516	412	292	181
Active drug	755	619	507	392	286	186

Incidence et valeurs absolues de la mort subite cardiaque en population



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

Revue complète de la littérature en appliquant la check-list de l'EHRA (29 critères) dans trois domaines en rythmologie

Checklist item	Intro		Methods													Regulatory				Open science		Results							
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
AI in Afib (n = 31)	100%	100%	100%	87%	71%	90%	35%	100%	84%	100%	100%	87%	42%	65%	97%	45%	87%	87%	48%	35%	6%	45%	77%	100%	58%	100%	55%	97%	87%
AI in SCD (n = 18)	44%	67%	94%	94%	100%	100%	78%	72%	78%	89%	100%	78%	56%	50%	56%	22%	61%	78%	94%	17%	28%	83%	39%	78%	28%	67%	50%	67%	94%
AI in the EP lab (n = 6)	100%	100%	100%	100%	67%	100%	67%	83%	100%	100%	100%	33%	17%	17%	83%	50%	67%	100%	100%	67%	33%	100%	83%	67%	17%	67%	50%	33%	100%

Lorsque plus de 85% d'un critère est atteint, il est considéré comme valide.

Exemple de critères: taille de l'échantillon, qualité des données, validation interne, externe, qualité du comparateur etc...

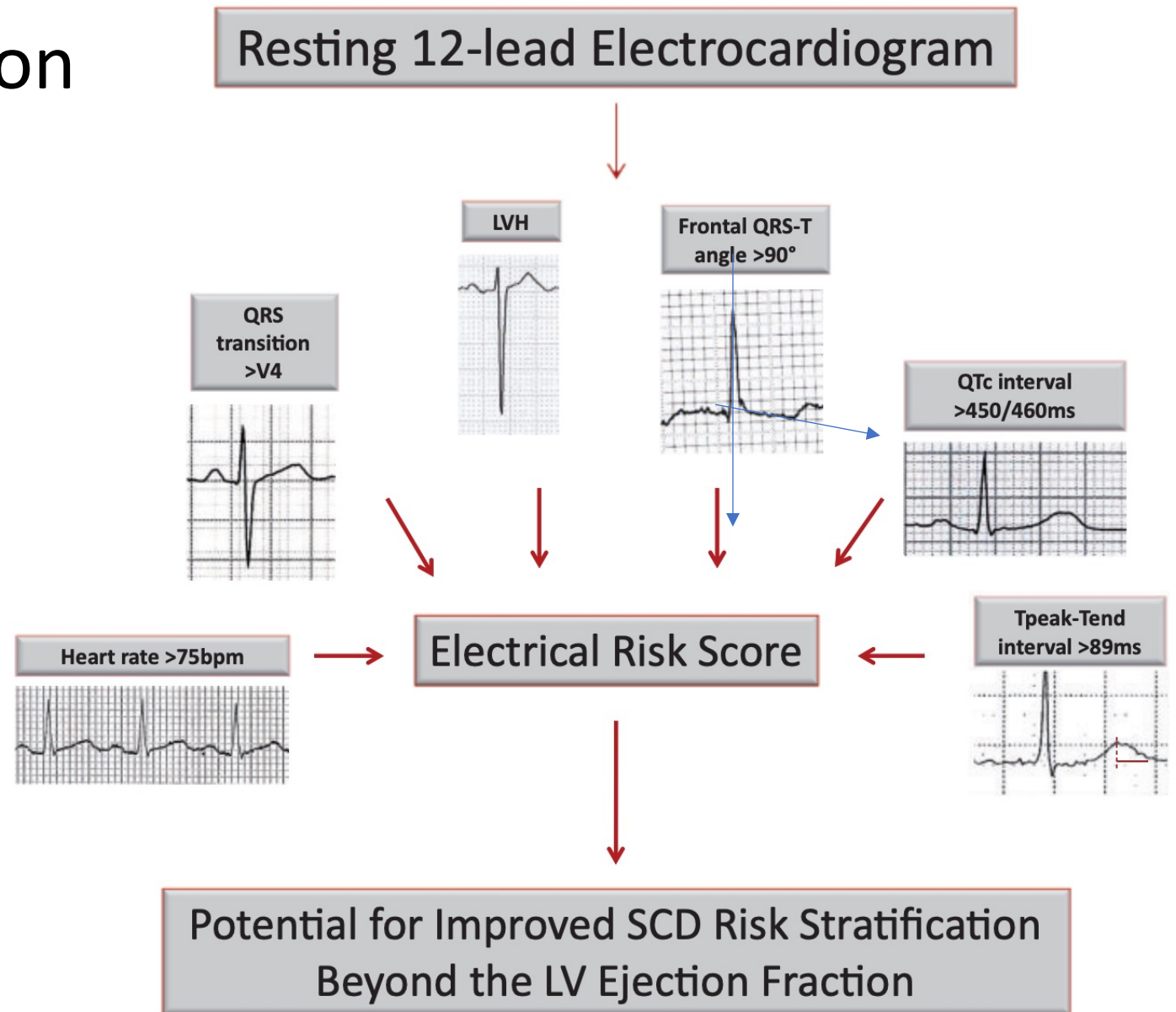
Au-delà de la FE

Electrical risk score **beyond** the left ventricular ejection fraction: prediction of sudden cardiac death in the Oregon Sudden Unexpected Death Study and the Atherosclerosis Risk in Communities Study

Aapo L. Aro^{1,2†}, Kyndaron Reinier^{1†}, Carmen Rusinaru¹, Audrey Uy-Evanado¹, Navid Darouian¹, Derek Phan¹, Wendy J. Mack³, Jonathan Jui⁴, Elsayed Z. Soliman⁵, Larisa G. Tereshchenko⁴, and Sumeet S. Chugh^{1*}

6 Paramètres de prédiction de la MSC

- 522 cas de MSC (65.3 ± 14.5 ans, 66% hommes) comparés à:
- 736 patients contrôles de la même région
- Suivi moyen 14 ans



Critères ECG et Odds ratio

ECG pattern	Cases (n = 522)	Controls (n = 736)	Odds ratio (95% CI)	P-value
Heart rate >75bpm	266 (51%)	167 (23%)	3.5 (2.8–4.5)	<0.001
QRSd >110 ms	72 (14%)	57 (8%)	1.9 (1.3–2.8)	<0.001
Prolonged QTc ^a	247 (47%)	114 (15%)	4.9 (3.8–6.4)	<0.001
Tpeak-Tend >89 ms	219 (42%)	188 (26%)	2.1 (1.7–2.8)	<0.001
QRS-T angle >90°	142 (27%)	103 (14%)	2.3 (1.7–3.1)	<0.001
Delayed QRS transition zone	147 (28%)	123 (17%)	2.0 (1.5–2.6)	<0.001
Electrocardiographic LVH	83 (16%)	59 (8%)	2.2 (1.5–3.1)	<0.001
Delayed intrinsicoid deflection	104 (20%)	107 (15%)	1.5 (1.1–2.0)	0.01

a QTc >450 ms in men and >460 ms in women.

Caractéristiques cliniques des patients avec MSC en fonction du score basé sur les critères ECGs

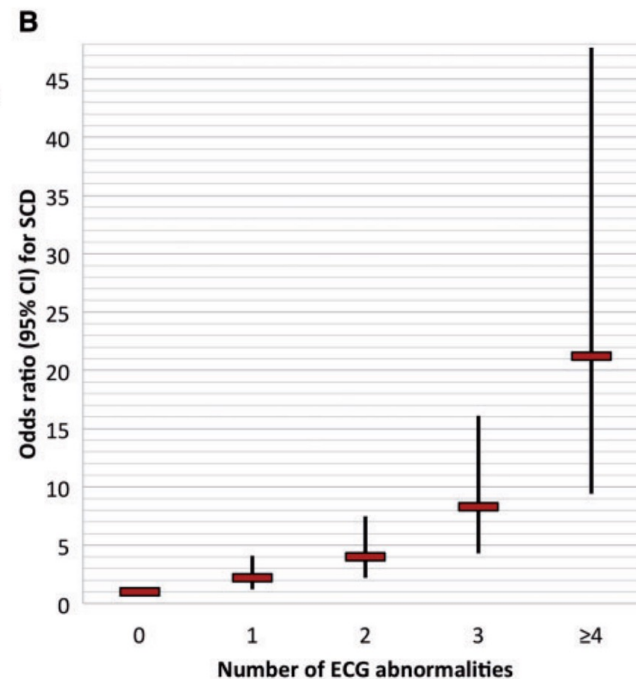
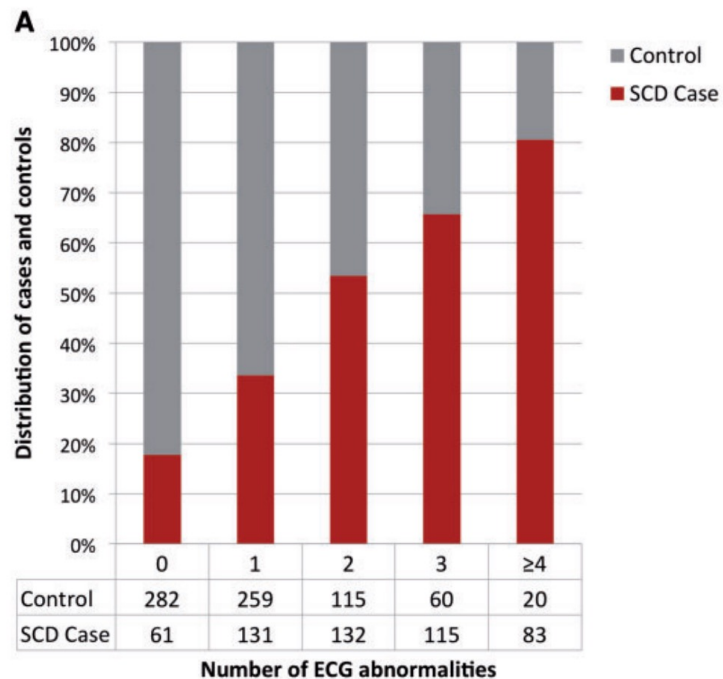
	Score 0 (n = 343)	Score 1 (n = 390)	Score 2 (n = 247)	Score 3 (n = 175)	Score ≥ 4 (n = 103)	P-value
Age, years	65.6 $\pm$ 11.5	65.3 $\pm$ 13.4	65.3 $\pm$ 12.8	65.6 $\pm$ 13.6	67.1 $\pm$ 13.9	0.44
Male	234 (68%)	284 (73%)	156 (63%)	111 (63%)	64 (62%)	0.04
Current smoker ^a	70 (25%)	73 (25%)	70 (38%)	48 (34%)	28 (35%)	0.007
Diabetes	78 (23%)	105 (27%)	88 (36%)	73 (42%)	49 (48%)	<0.001
Hypertension	225 (66%)	252 (65%)	188 (76%)	134 (77%)	81 (79%)	<0.001
History of coronary artery disease	164 (48%)	172 (44%)	135 (55%)	96 (55%)	73 (71%)	<0.001
Body mass index (kg/m ²) ^b	29.0 $\pm$ 7.1	30.3 $\pm$ 7.6	31.3 $\pm$ 8.3	30.3 $\pm$ 8.3	29.7 $\pm$ 8.7	0.09

NB:

- *Smoking history missing for 112 cases and 166 controls.*
- *Body mass index missing for 116 cases and 26 controls.*

A. Distribution des critères ECGs entre MSC et CTRL

B. Risque cumulé de MSC ajusté (à l'âge, le sexe, l'HTA, diabète, FEVG)



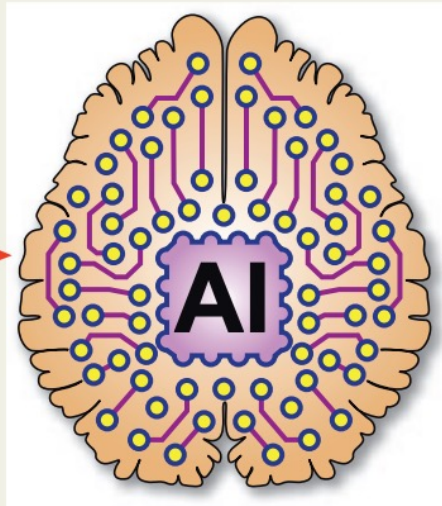
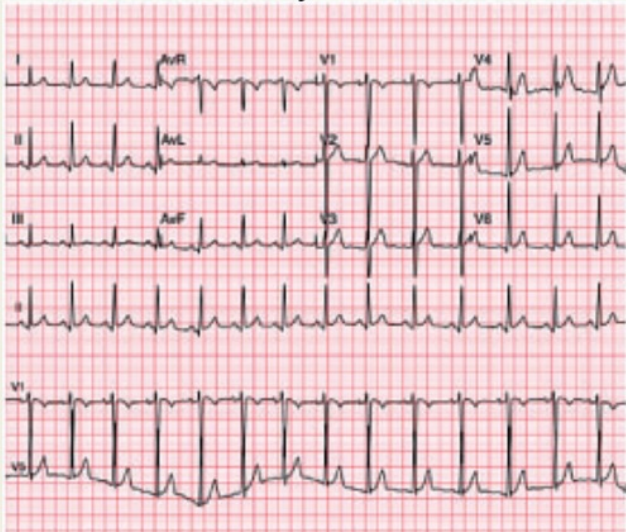
Sujets avec ≥ 4 anomalies ECG avait un OR de **21.2** pour la MSC [95% confidence interval (CI) 9.4–47.7; $P < 0.001$].

Dans le sous groupe FE $>35\%$, the OR est de **26.1** (95% CI 9.9–68.5; $P < 0.001$).

Application of artificial intelligence to the electrocardiogram

Zachi I. Attia ¹, David M. Harmon ², Elijah R. Behr ^{3,4}, and Paul A. Friedman^{1*}

Normal sinus rhythm Normal ECG



Current Rhythm

AF in NSR

Low Ejection Fraction

Valvular Diseases

Channelopathies

Hypertrophic Cardiomyopathy

Review

A Review of the Integration of Artificial Intelligence in Cardiac Electrophysiology

- Détection infraclinique des arythmies (FA, TV)
- Guidage dans l'ablation des tachycardies (FA)
- Indication des DAI/Resynchronisation
- Prédiction de la MSC**
- Détection des anomalies génétiques
- Détection infraclinique des anomalies structurelles et rythmiques

L'ECG en plus des critères cliniques habituels



<https://doi.org/10.1038/s43856-024-00451-9>

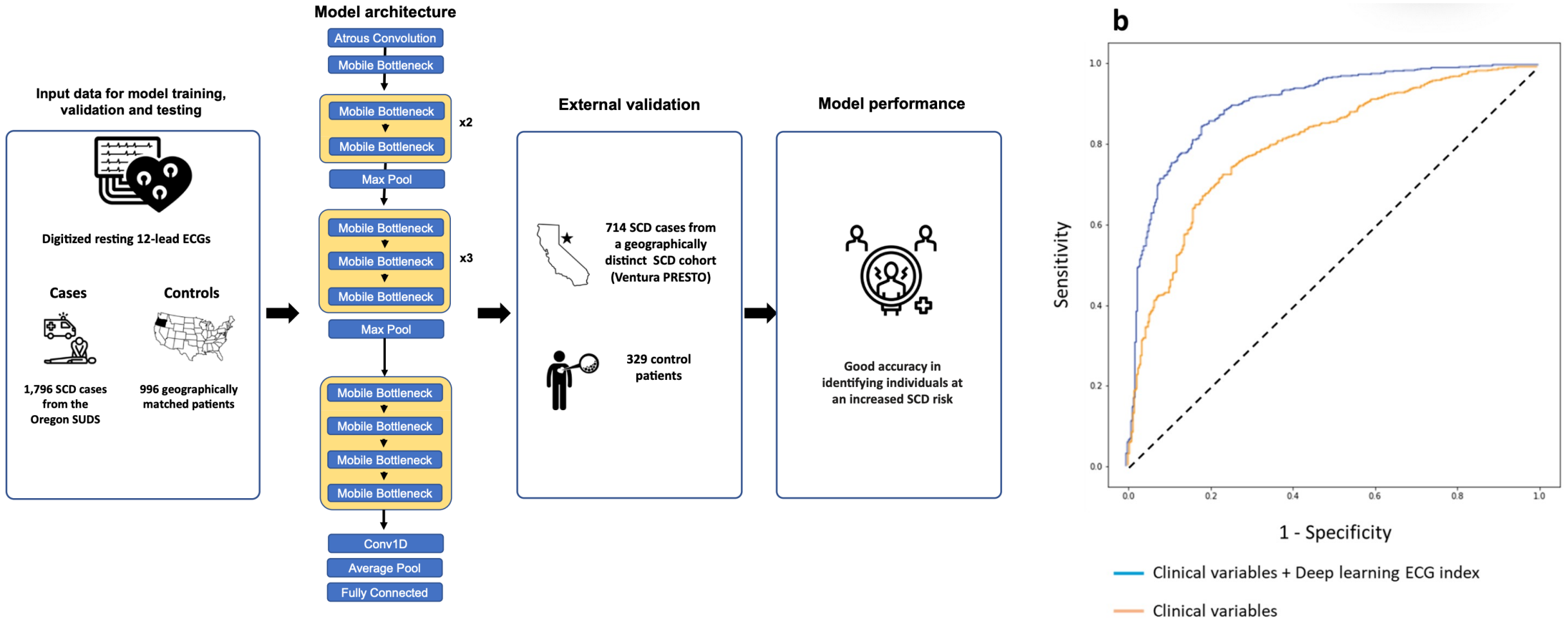
An ECG-based artificial intelligence model for assessment of sudden cardiac death risk



Check for updates

Lauri Holmstrom¹, Harpriya Chugh¹, Kotoka Nakamura ¹, Ziana Bhanji¹, Madison Seifer¹,
Audrey Uy-Evanado¹, Kyndaron Reinier ¹, David Ouyang ^{1,2} & Sumeet S. Chugh^{1,2}

Utiliser « tout » l'ECG numérique plutôt que des critères prédéfinis

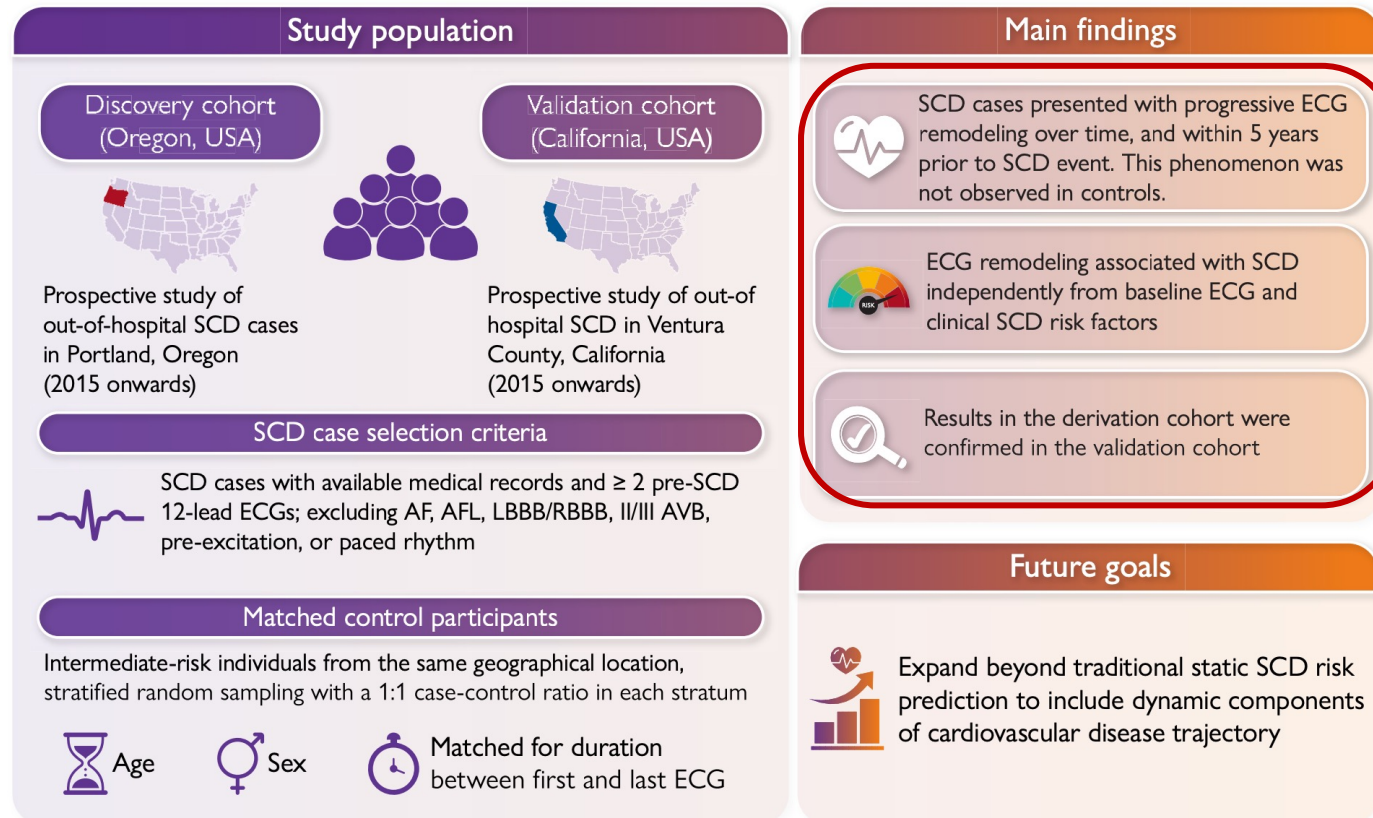
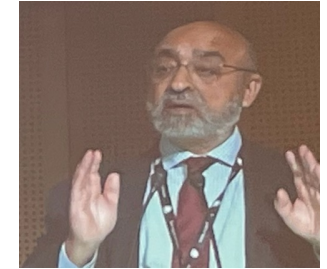


Au delà des Facteurs de Risque habituels: âge, sexe, IC, CAD, IDM, Diabète, BPCO, AVC, épilepsie

La dynamique des modifications ECG

Dynamic electrocardiogram changes are a novel risk marker for sudden cardiac death

Hoang Nhat Pham^{1†}, Lauri Holmstrom^{1†}, Harpriya Chugh¹, Audrey Uy-Evanado¹, Kotoka Nakamura¹, Zijun Zhang², Angelo Salvucci³, Jonathan Jui⁴, Kyndaron Reinier¹, and Sumeet S. Chugh ^{1,2*}



Matched control participants

Intermediate-risk individuals from the same geographical location, stratified random sampling with a 1:1 case-control ratio in each stratum

 Age

 Sex

 Matched for duration between first and last ECG

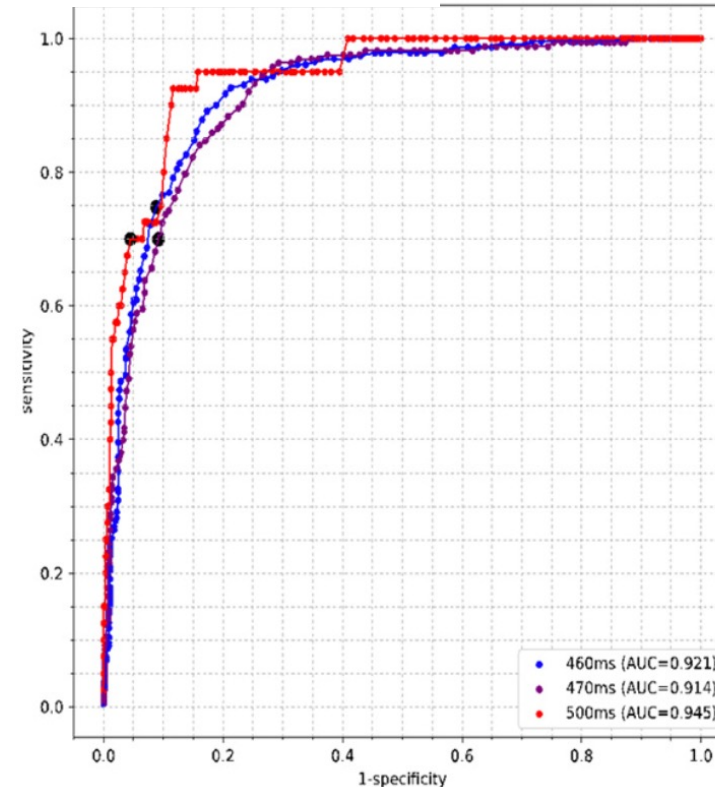
 Future goals Expand beyond traditional static SCD risk prediction to include dynamic components of cardiovascular disease trajectory |

QT et dyskaliémie

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

Mesure du QT: Performance identique d'une IA avec ECG 2D vs analyse experte d'un ECG 12D

1.6 million 12-lead ECGs



AUC indicates area under curve; DNN, deep neural network; mECG, mobile ECG; QTcB, Bazett's heart rate–corrected QT interval; NPV, negative predictive value; and PPV, positive predictive value.

A Deep-Learning Algorithm (ECG12Net) for Detecting Hypokalemia and Hyperkalemia by Electrocardiography: Algorithm Development

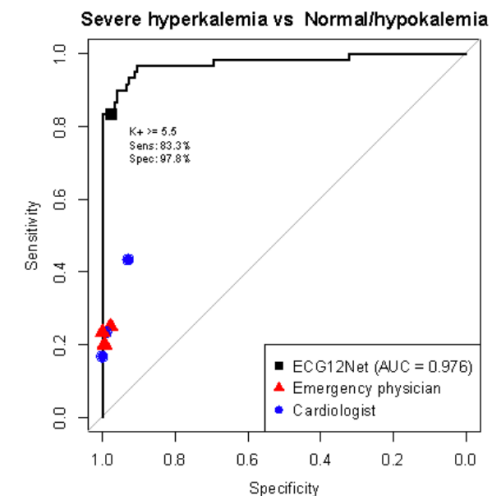
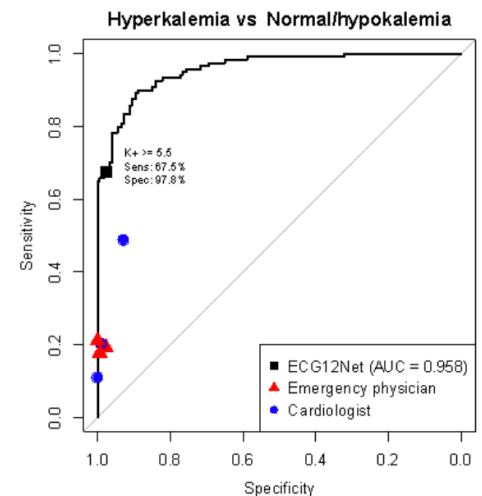
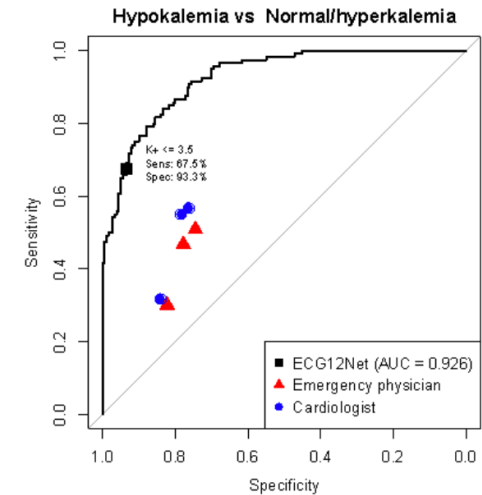
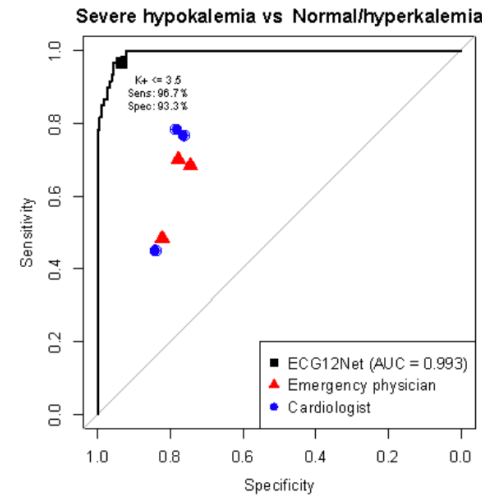
« Compétition homme vs machine »

- Sévère HypoK⁺ (<2.5):

Cardiologues/urgentistes : SS: 45%-78.3% and SP 74.4%-83.9%, vs
ECG12Net-1 : SS 96.7% (95% CI 91.7-100.0), SP: 93.3% (95% CI 89.4-96.7).

- Sévère hyper + (>6.5) :

Cardiologues/urgentistes : SP : 92.8%-100.0, mais SS 16.7%-43.3%
ECG12Net-1 :SS: 83.3% (95% CI 73.3-91.7) , SP: 97.8% (95% CI 95.6-99.4).



Les données les plus récentes

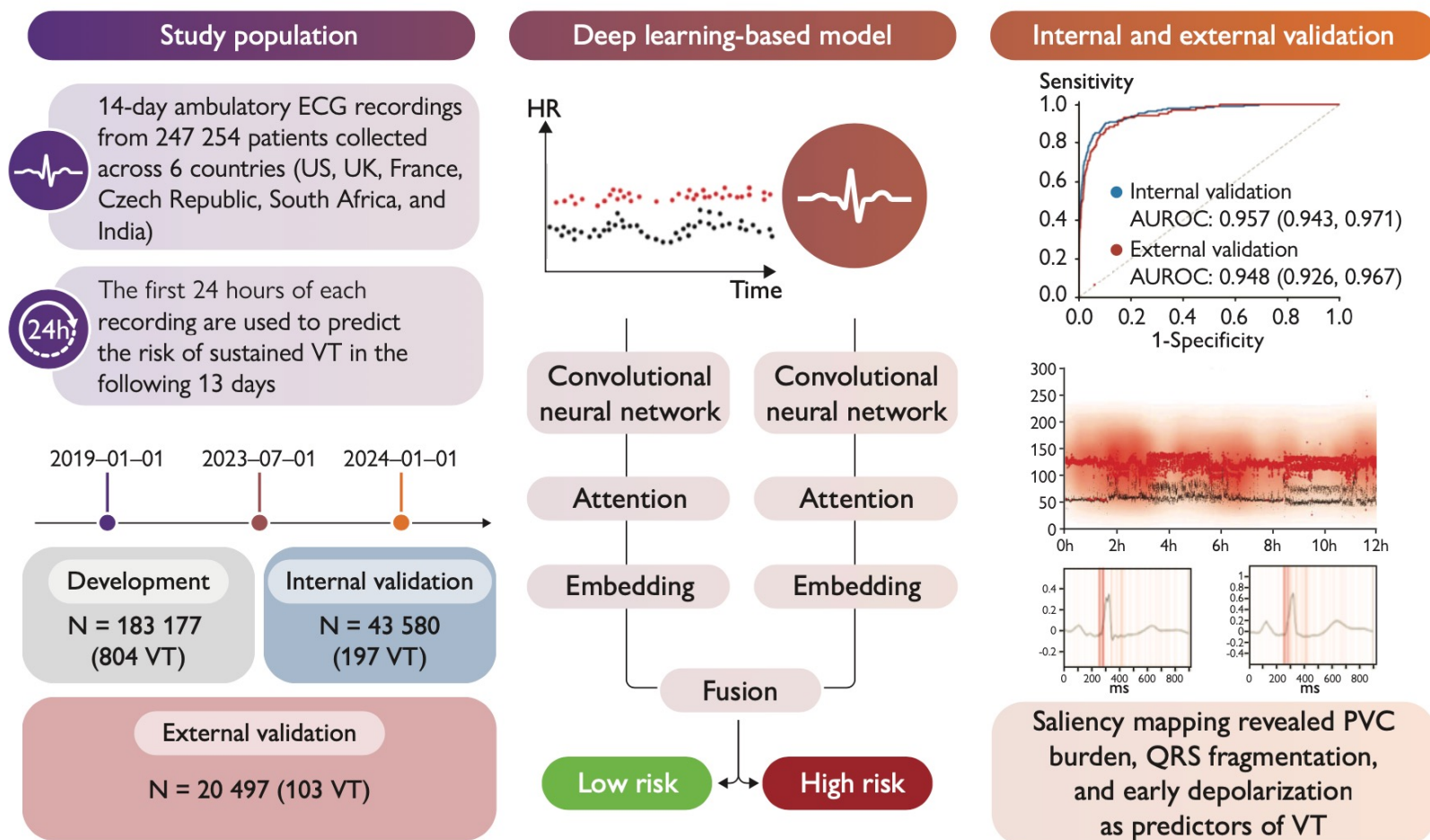
Near-term prediction of sustained ventricular arrhythmias applying artificial intelligence to single-lead ambulatory electrocardiogram

Laurent Fiorina ^{1,2,†}, Tanner Carbonati^{3,†}, Kumar Narayanan ^{2,4}, Jia Li³, Christine Henry³, Jagmeet P. Singh⁵, and Eloi Marijon ^{2,6,*}

- ✓ Critères prédictifs:
 - ✓ Charge en ESV
 - ✓ Fragmentation du QRS
 - ✓ Dépolarisation ventriculaire précoce

- ✓ **Système Holter** une dérivation
- Possibilité d'intégration dans un objet connecté/montre*

SP 90%
SS 71%





ESC

European Journal of Preventive Cardiology (2026) 00, 1–12

<https://doi.org/10.1093/eurjpc/zwag087>

FULL RESEARCH PAPER

Machine learning & artificial intelligence

Machine learning-based prediction of sudden cardiac death in the general population using electronic health record data

Younès Youssfi^{1,2,3†}, Richard Chocron ^{1,2,4†}, Thomas Laurenceau ^{1,2,4},
Frankie Beganton ^{1,2}, Jean-Philippe Empana ^{1,2}, Tom Rea⁵, Nicolas Chopin ³,
Wulfran Bougouin ^{1,2,6}, and Xavier Jouven ^{1,2,7*}

¹Université Paris Cité, Inserm, PARCC, F-75015 Paris, France; ²Paris Sudden Death Expertise Center, Paris, France; ³National School for Statistics and Economic Administration, Polytechnic Institute of Paris, Paris, France; ⁴Emergency Department, European Georges Pompidou Hospital, Paris, France; ⁵Department of Medicine (Emergency Medicine), University of Washington, Seattle, USA; ⁶Intensive Care Unit, Jacques Cartier Hospital, Massy, France; and ⁷Cardiology Department, European Georges Pompidou Hospital, 20 rue Leblanc, 75015, Paris, France

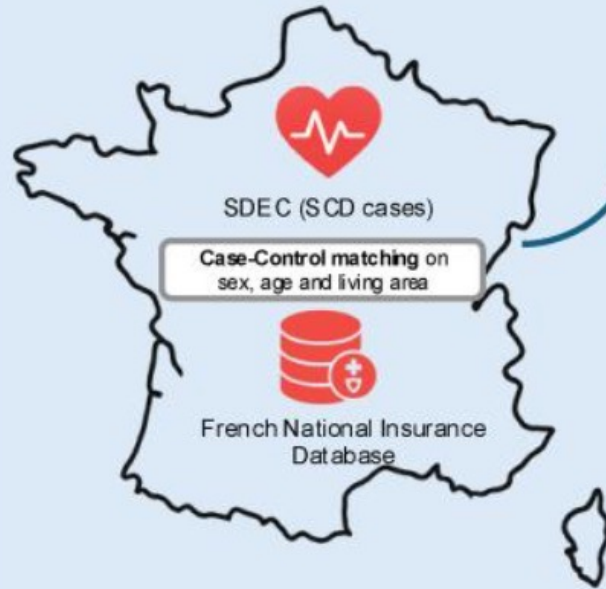
Received 4 August 2025; revised 5 November 2025; accepted 8 January 2026; online publish-ahead-of-print 6 March 2026

Machine Learning-Based Prediction of Sudden Cardiac Death in the General Population Using EHR Data

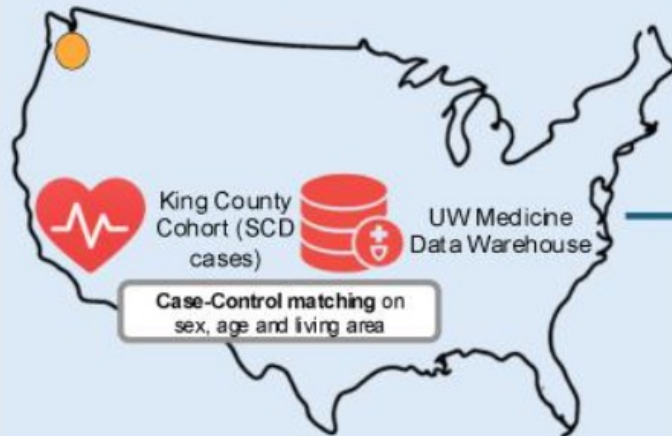
Data collection

Data preparation

Model training



5-years medical history
for each patient



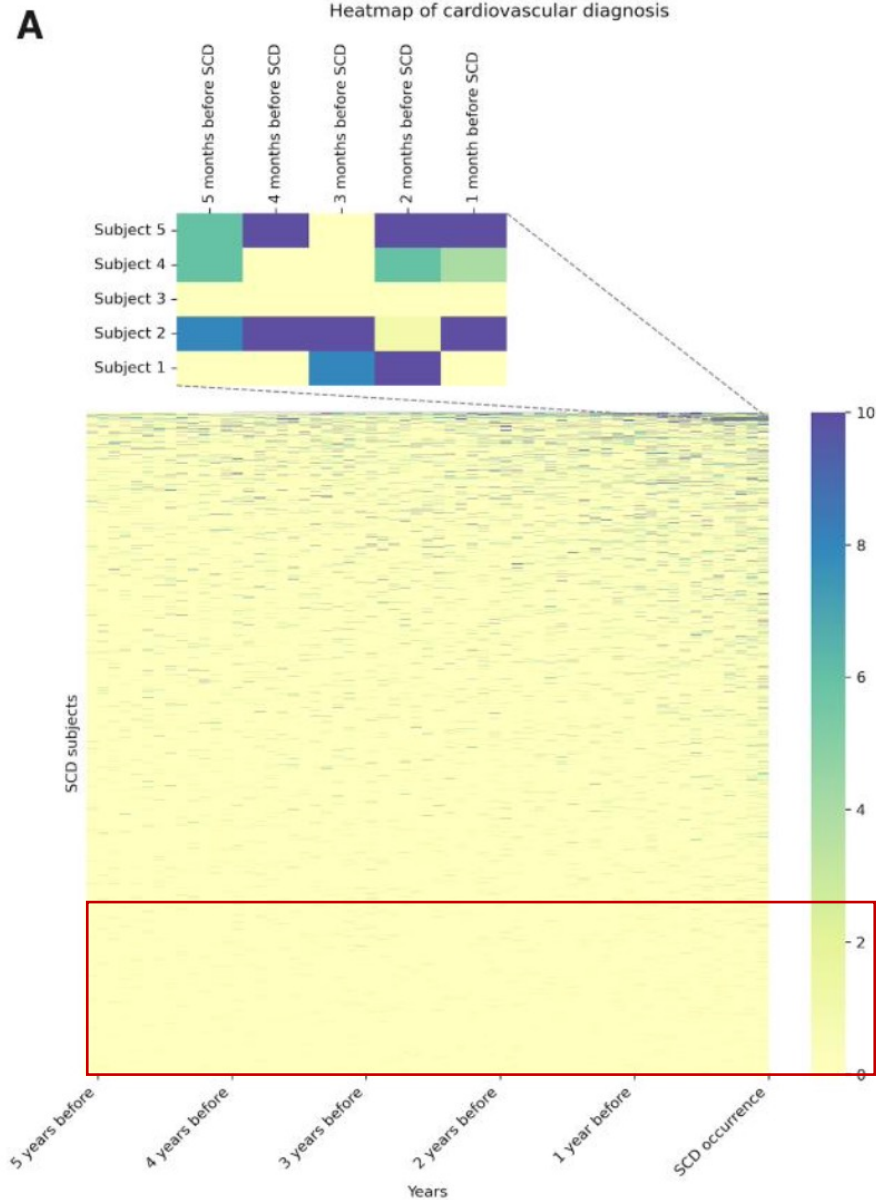
5-years medical history
for each patient



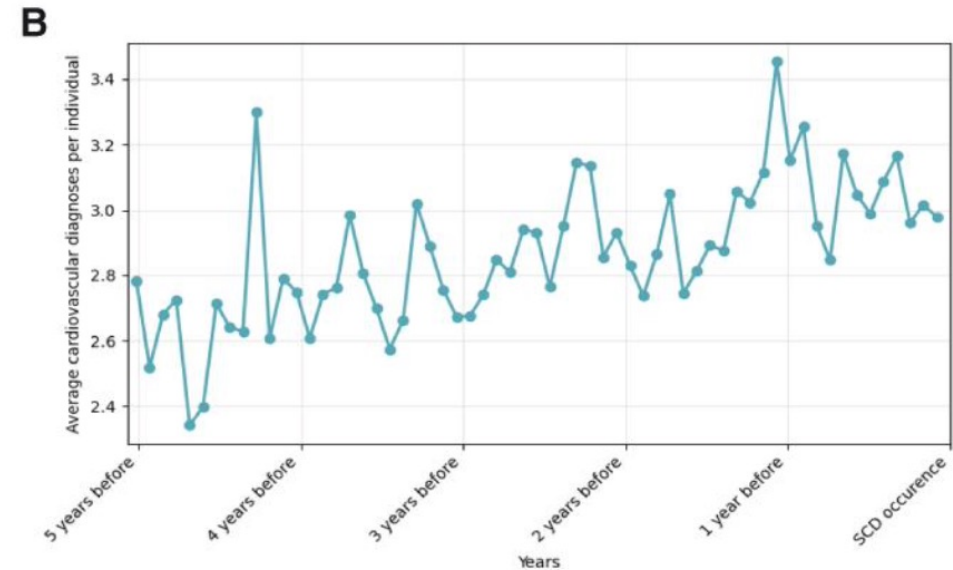
Derivation Cohort
SDEC 2011-2015

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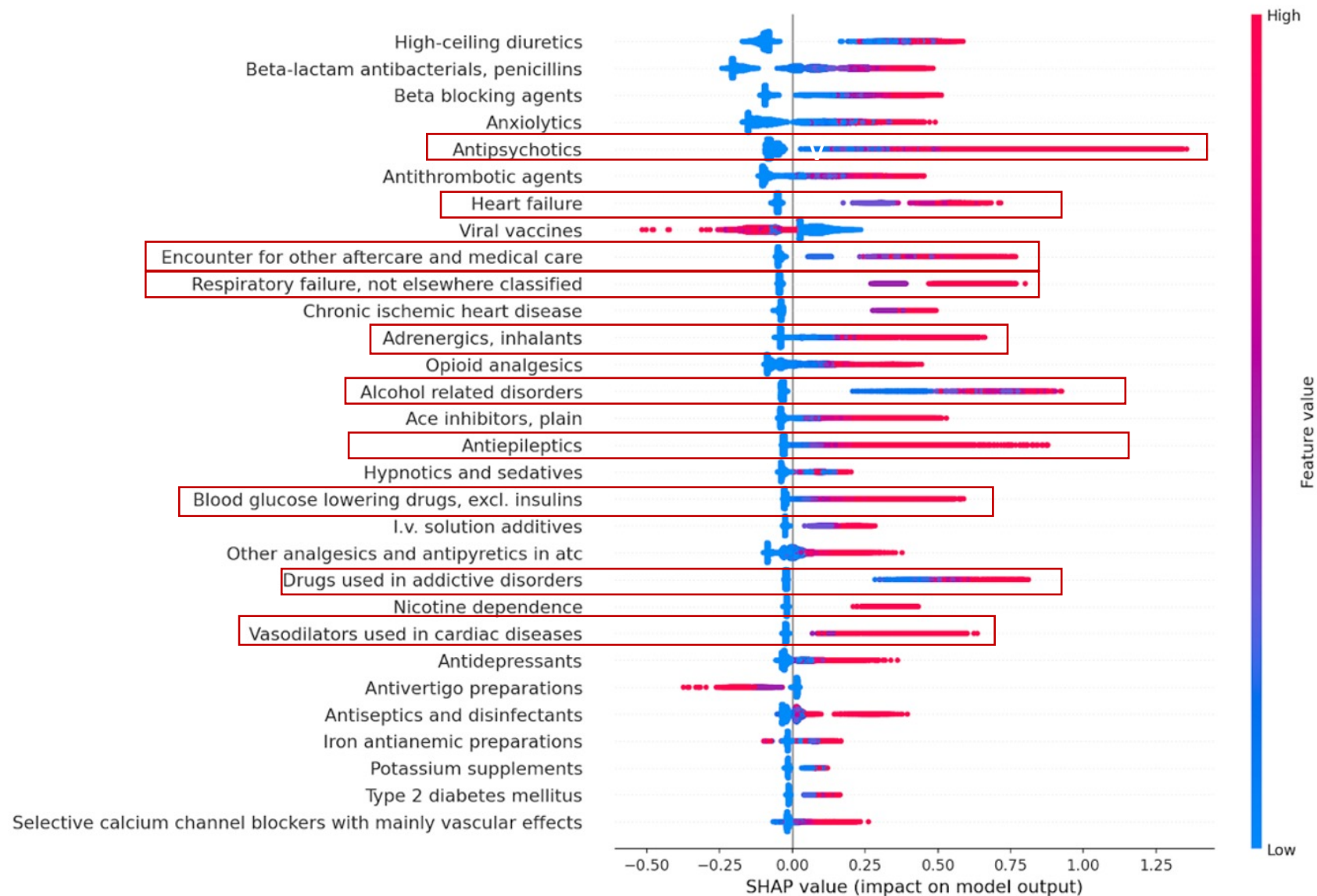
Model speci
and selec



Distribution temporelle des
« diagnostics/évènements »
cardiovasculaires pour chaque
patient précédant la MSC



Importance du poids des variables dans le modèle prédictif



En conclusion

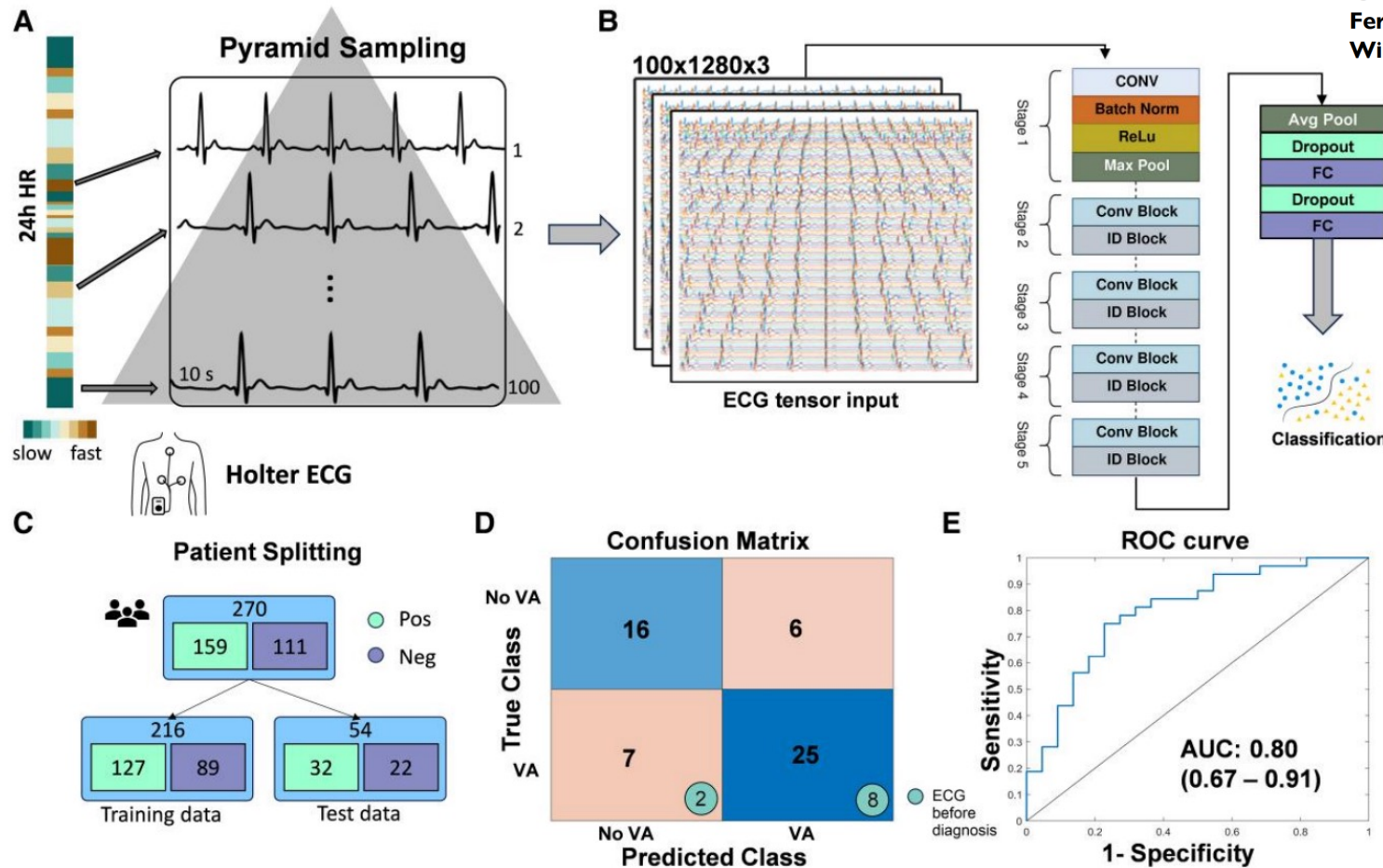
- l'IA peu contribuer à la prédiction des évènements, mais aussi à une meilleure compréhension des mécanismes menant aux arythmies ventriculaires.
- Est-ce qu'un ECG 12D (ou une seule dérivation) permet à lui seul d'identifier le risque de MSC dans la population générale ? oui mais...
- Comparé à une « prévention statique », une prévention dynamique, multiparamétrique à long termes est plus efficace,
- La VPP reste basse environ 15% (rareté des évènements, source de faux positifs)
- Questions organisationnelles et éthiques : fréquence et modalités des alertes, organisation de la réponse médicale, risque d'anxiété anticipatoire, et évaluation du rapport coût-efficacité.

Merci de votre attention

Gabriel.Laurent@chu-Dijon.fr

Artificial intelligence for ventricular arrhythmia capability using ambulatory electrocardiograms

Joseph Barker ^{1,2,3,4,5,*†}, Xin Li ^{1,6,†}, Ahmed Kotb ^{1,2}, Akash Mavilakandy², Ibrahim Antoun^{1,3}, Chokanan Thaitirarot¹, Ivelin Koev^{1,2}, Sharon Man^{1,2}, Fernando S. Schlindwein ^{4,6}, Harshil Dhutia^{1,2}, Shui Hao Chin^{1,2}, Ivan Tyukin ⁷, William B. Nicolson^{1,2}, and G. Andre Ng ^{1,2,4}



Open-source VA-ResNet-50 deep neural network

Artificial intelligence (AI)	A branch of computer science focused on creating algorithms with the aim of performing tasks usually requiring human intelligence, such as recognizing patterns, making decisions and predicting outcomes. AI can supersede human level intelligence in domain specific tasks
Open science in AI	The practice of promoting transparency, reproducibility, and accessibility in artificial intelligence research through open sharing of data, code, and methodologies to enhance collaboration and accelerate innovation in the field.
Machine learning (ML)	A subset of AI where algorithms learn patterns from data to make predictions or perform classifications (binary or multi-class) without explicit programming for each task. ML includes supervised learning, where specific labels are defined by the user, as well as unsupervised learning, which identifies patterns and structures in data without predefined labels. In EP, ML models are used to diagnose arrhythmias, predict outcomes, and optimize arrhythmia treatment.
Deep learning (DL)	A subset of ML that uses artificial neural networks to process and analyse information, where the features of interest are learned directly from the data, and not defined by the user.
Artificial neural network (ANN)	A foundational method in AI that teaches computers to process data in a way that is inspired by the human brain, using interconnected nodes or 'neurons' in a layered structure. It provides a means for dealing with complex pattern-oriented tasks, including classification, regression and pattern recognition. The nonparametric nature of ANN enables models to be developed without having any prior knowledge of the distribution of the data population or possible interaction effects between variables as required by commonly used parametric statistical methods.
Deep neural network (DNN)	A DNN is a neural network with multiple layers between the input and output layers required for high dimensional data analysis. DNNs encompass a variety of architectures designed for different tasks.