Artificial Intelligence in Cardiology and Electrophysiology

6TH MYANMAR CARDIOLOGY CONFERENCE

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Artificial Intelligence in Cardiology and Electrophysiology

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MANILA, PHILIPPINES

Towards Holistic & Comprehensive Cardiac Care


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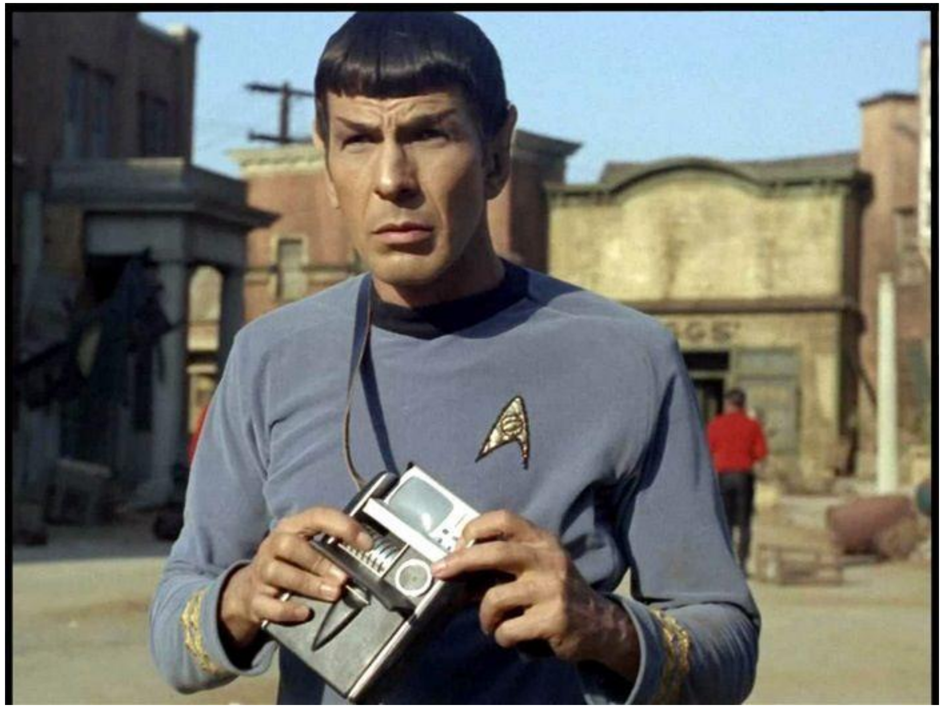
Disclosures of Conflicts

- I have no conflicts of interests relevant to this talk
- I have no investment in medical, device and AI technology companies

“Human intelligence can be so precisely described that a machine can be made to simulate it.”

1956 Dartmouth Summer Research Project on Artificial Intelligence


STAR TREK

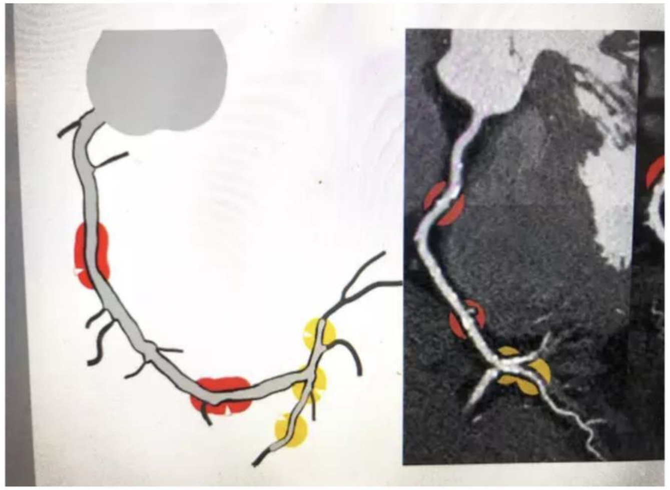


Artificial Intelligence in Cardiology and Cardiac Electrophysiology

As of August 2024, the FDA has authorized 950 AI/ML enabled medical devices, 98 are specifically designed for cardiology.

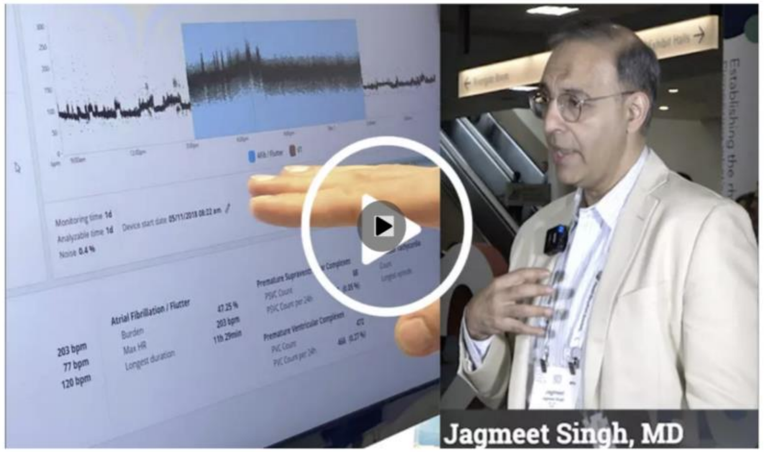
Cardiology has embraced AI more than most other specialties

Dave Fornell | May 12, 2023 | Cardiovascular Business | Artificial Intelligence



AI gaining popularity in electrophysiology

Dave Fornell | May 24, 2023 | Cardiovascular Business | Artificial Intelligence



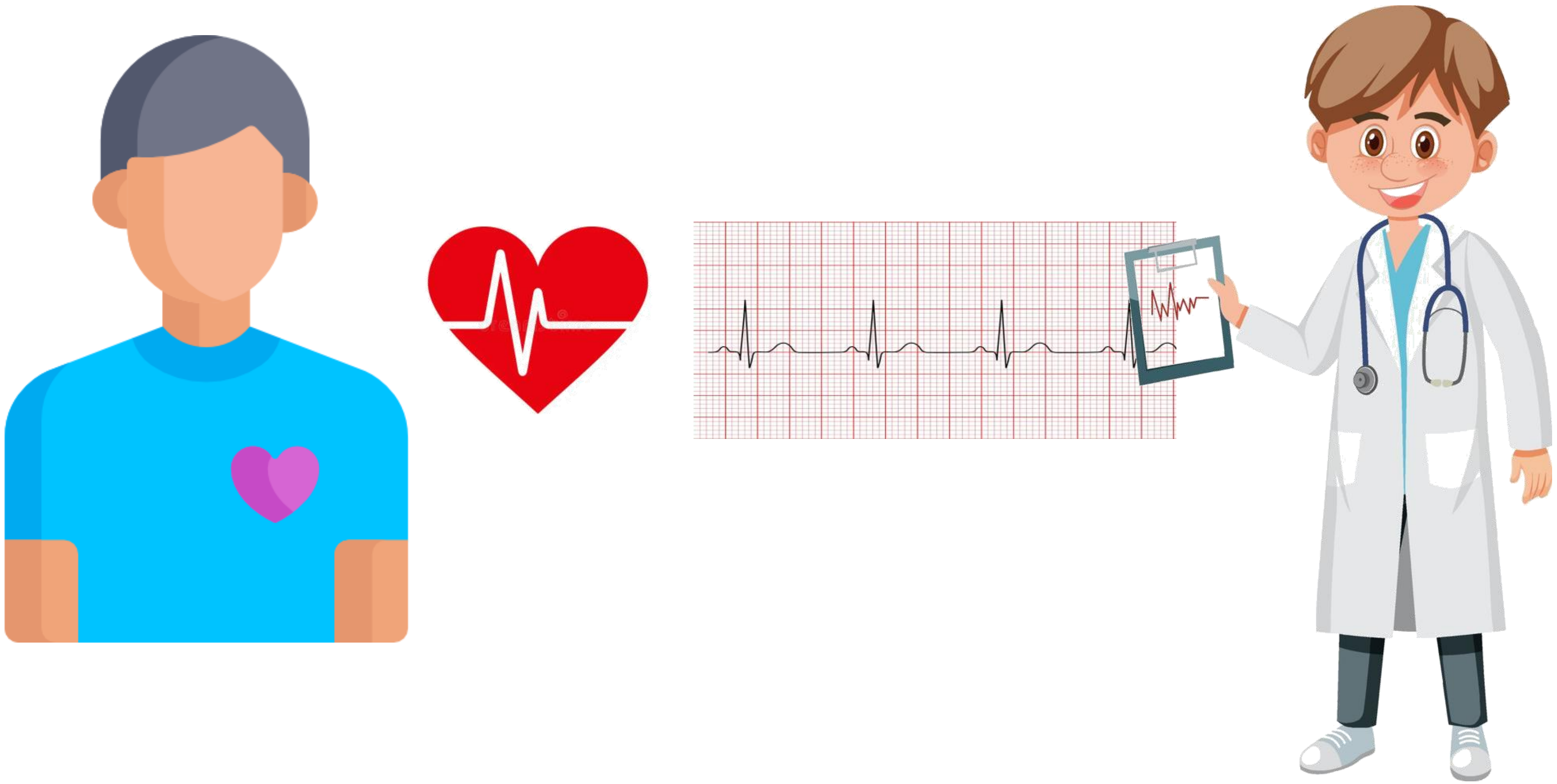
The proliferation of artificial intelligence (AI) in healthcare includes numerous algorithms for electrophysiology (EP), and several have already been commercialized in the Unites States. Jagmeet Singh, MD, professor of medicine at Harvard Medical School and founding director of the Resynchronization and Advanced Cardiac Therapeutics Program at Mass General Hospital, spoke with Cardiovascular Business at Heart Rhythm 2023 to explain how AI is being used in EP.

<u>Google scholar:</u>

“Artificial intelligence” – 7,090,000 results

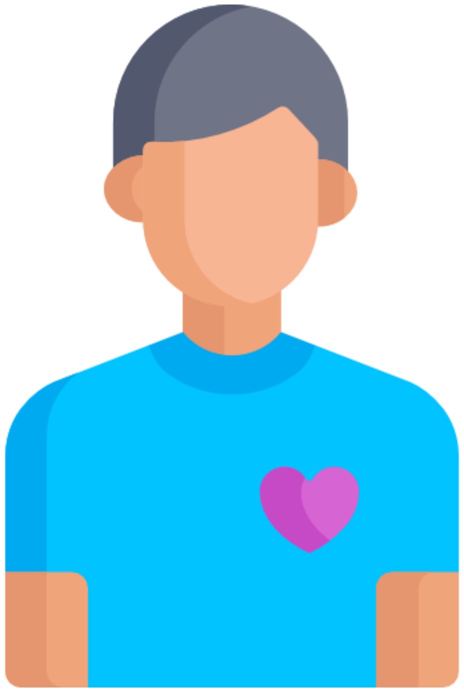
“Aspirin’ – 1,580,000 results

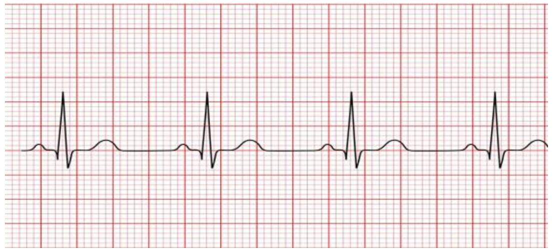
Current care scenario



Doctor
Interprets test
Advises patient on diagnosis
Gives plan and treatment

Imagine this scenario





Diagnosis
Risk of heart disease
Risk of future heart attack
Probability of sudden death
Risk of heart failure
Metabolic parameters
Lifespan
Etc. etc.

Definitions

- Artificial intelligence (AI)
  - Capability of a machine to imitate intelligent human behavior or perform tasks that typically require human intelligence
- Machine learning (ML)
  - Subset of AI in which computers learn from experience without explicit programming
- Deep learning (DL)
  - Subset of machine learning that uses artificial neural networks

Definitions

- Artificial neural networks (ANN)
  - Generic architecture for a mathematical model to teach computers to learn, inspired by the human brain’s neural structure
- Convolutional neural networks (CNN)
  - Type of deep learning algorithm optimized for processing grid-like data such as images by learning new features that distinguish them into different categories
- Algorithm
  - Set of mathematical procedures used to learn patterns from data

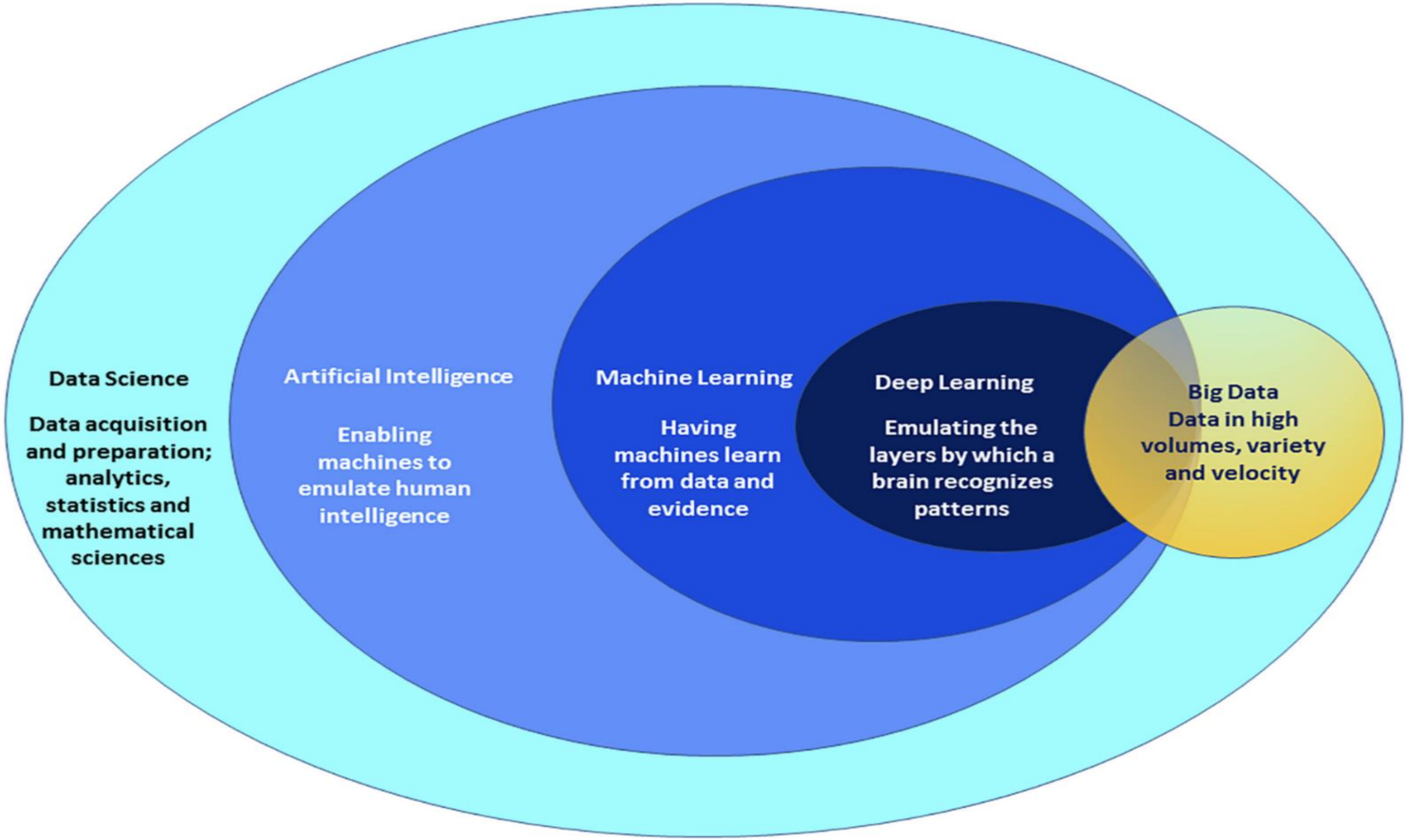
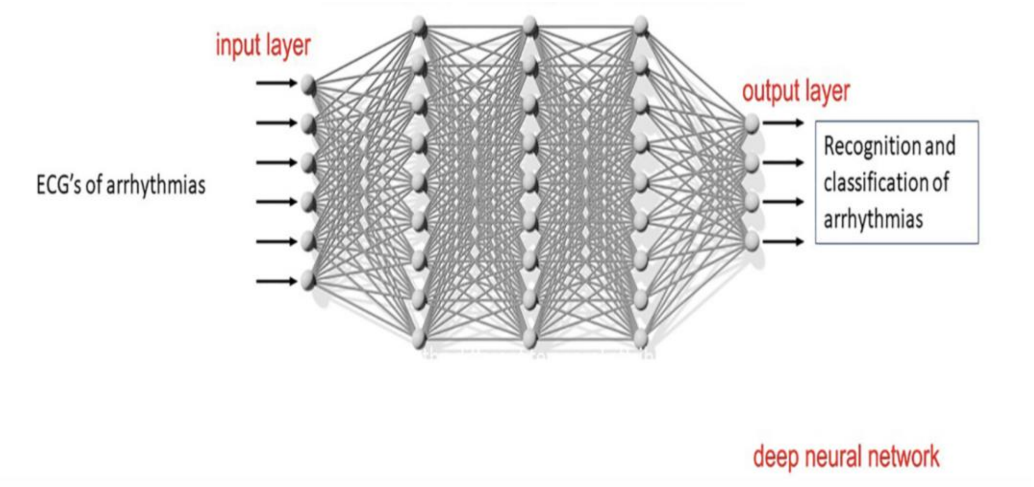


Figure 1 Positioning of disciplines commonly associated under the rubric of "AI." This includes data science, artificial intelligence, machine learning, deep learning, and big data. Data velocity refers to the speed in which data are generated, distributed, and collected.

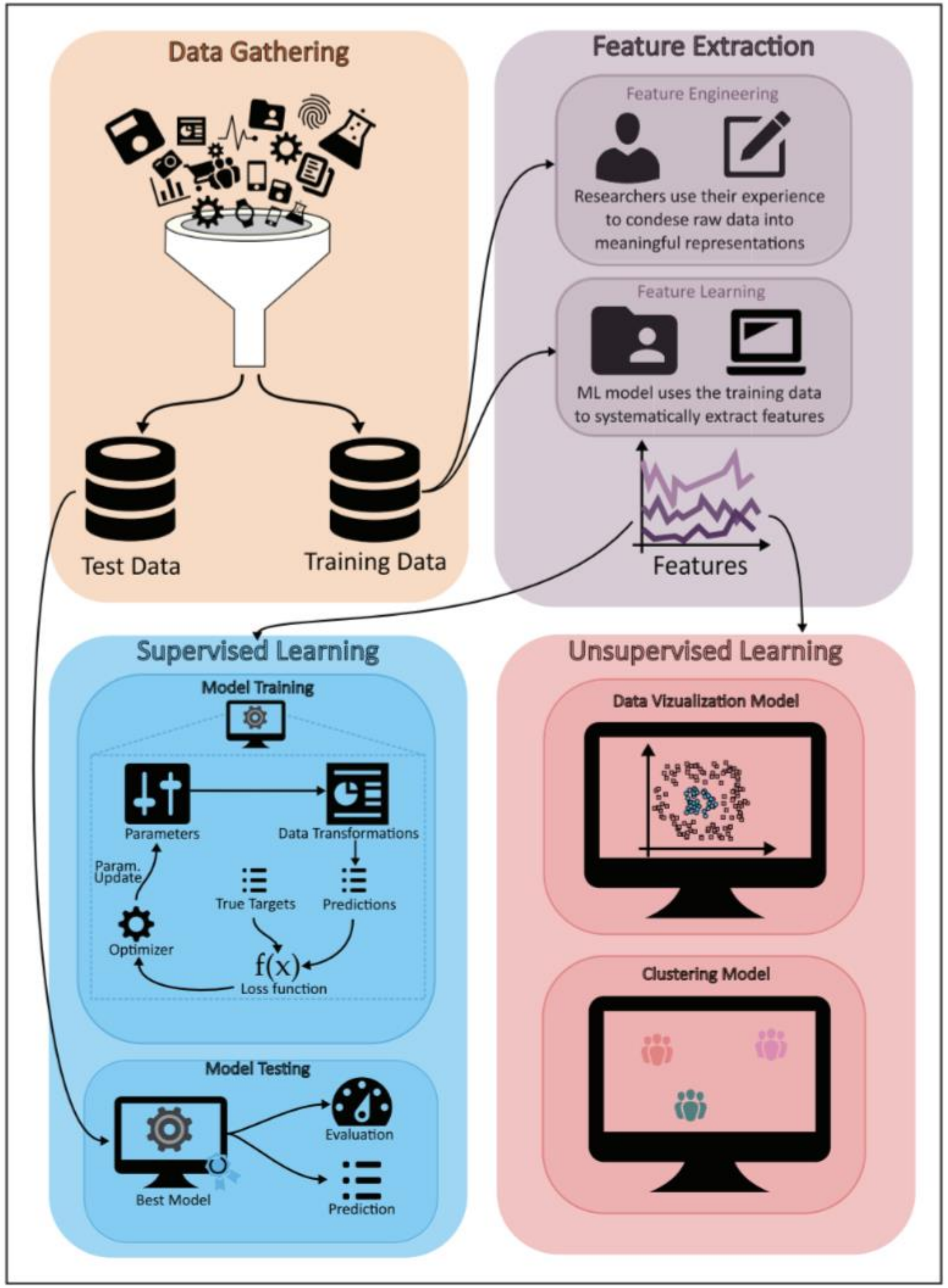


Real world:

Human expert interpretation

AI – Machine Learning:

Superior pattern recognition



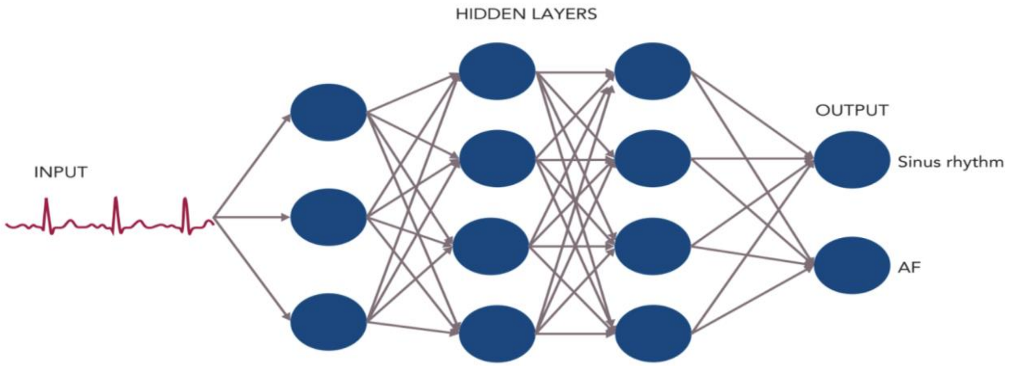
Machine Learning Workflow

DATA

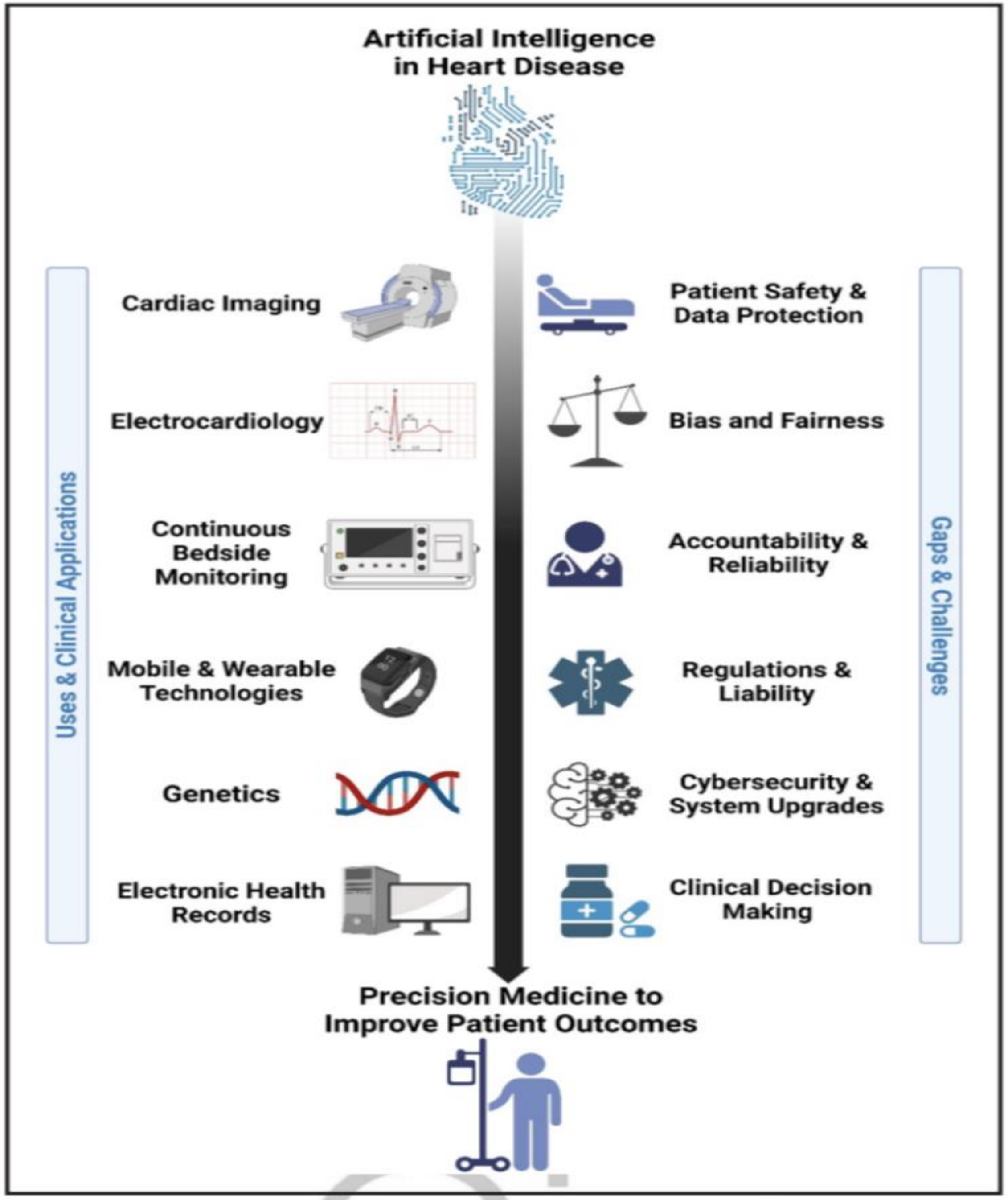
COMPUTER ANALYSIS

PATTERNS PROCESSING

Unsupervised Learning | **Supervised Learning** | **Reinforcement Learning**

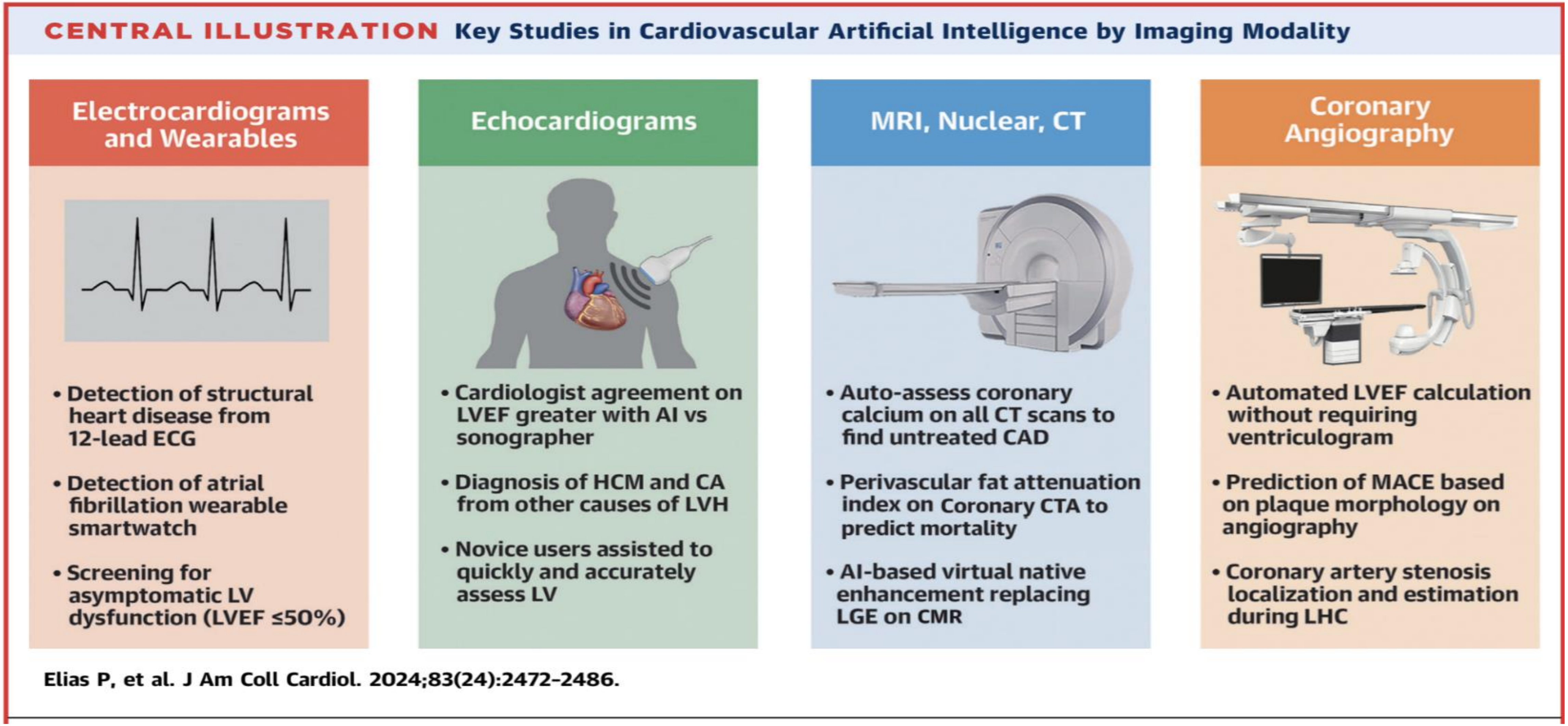


Trayanova N et al. Circ Res 2021;128:544-566

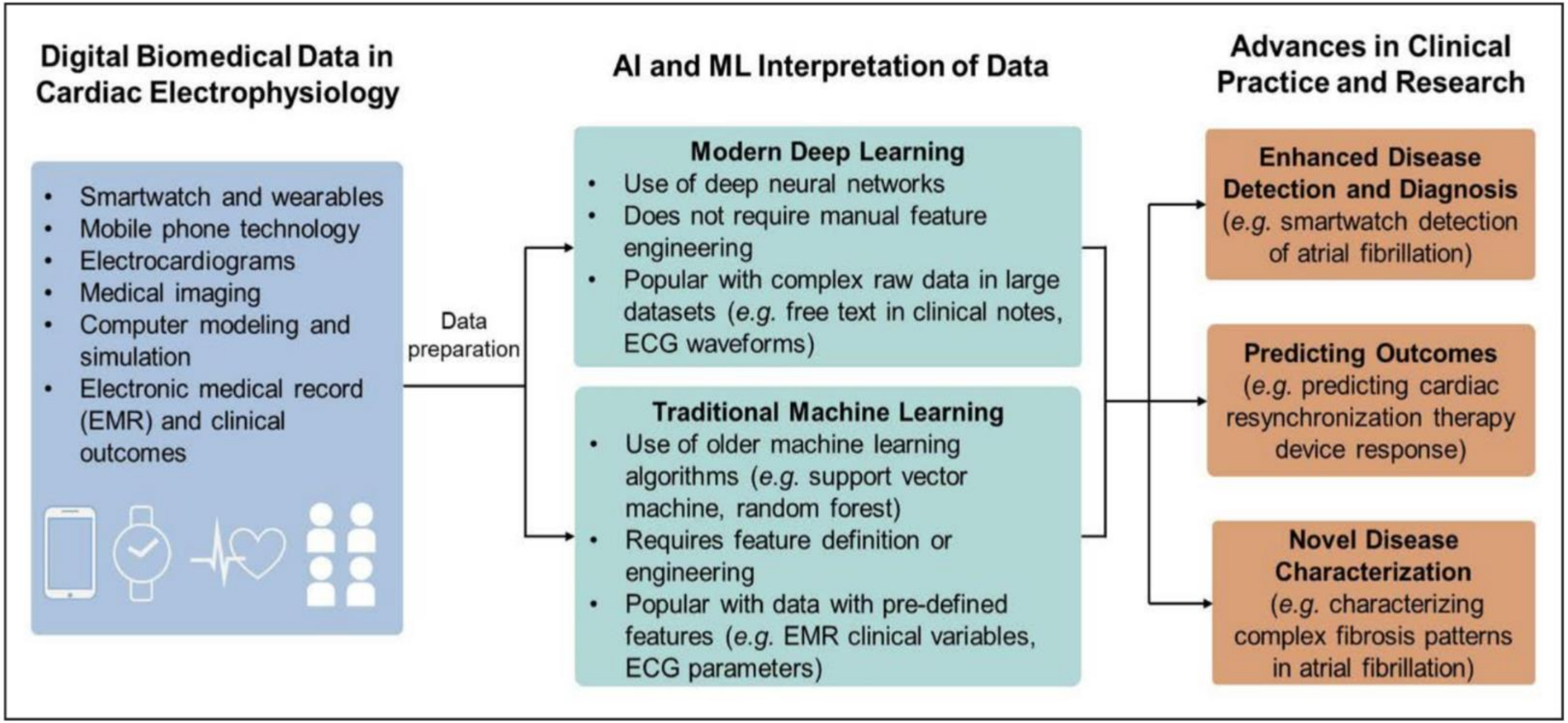


Armoundas A et al.Circulation. 2024;149

AI is transforming cardiovascular care, without us knowing it



Overview of AI in Cardiac Electrophysiology



Circ Arrhythm Electrophysiol. 2020;13:e007952

AI capabilities in Electrocardiography

1. Arrhythmia detection/diagnosis
2. Prediction of potential arrhythmias in sinus rhythm
3. Detection of arrhythmogenic syndromes
4. Prediction of sudden cardiac death/risk
5. Detection of structural heart disease
6. Prediction of future cardiovascular disease
7. Detection of occult conditions
8. Detection of miscellaneous medical conditions

Arrhythmia detection using AI in ECG

ARTICLE

https://doi.org/10.1038/s41467-020-15432-4 OPEN

Check for updates

Automatic diagnosis of the 12-lead ECG using a deep neural network

Antônio H. Ribeiro[1,2✉], Manoel Horta Ribeiro[1], Gabriela M. M. Paixão[1,3], Derick M. Oliveira[1], Paulo R. Gomes[1,3], Jéssica A. Canazart[1,3], Milton P. S. Ferreira[1], Carl R. Andersson[2], Peter W. Macfarlane[4], Wagner Meira Jr.[1], Thomas B. Schön[2✉] & Antonio Luiz P. Ribeiro[1,3✉]

AI interpretation of ECG outperformed physicians

Table 2 (Performance indexes) Scores of our DNN are compared on the test set with the average performance of: (i) 4th year cardiology resident (cardio.); (ii) 3rd year emergency resident (emerg.); and (iii) 5th year medical students (stud.).

	Precision (PPV)				Recall (Sensitivity)				Specificity				F1 score			
	DNN	cardio.	emerg.	stud.	DNN	cardio.	emerg.	stud.	DNN	cardio.	emerg.	stud.	DNN	cardio.	emerg.	stud.
1dAVb	0.867	0.905	0.639	0.605	0.929	0.679	0.821	0.929	0.995	0.997	0.984	0.979	**0.897**	0.776	0.719	0.732
RBBB	0.895	0.868	0.963	0.914	1.000	0.971	0.765	0.941	0.995	0.994	0.999	0.996	**0.944**	0.917	0.852	0.928
LBBB	1.000	1.000	0.963	0.931	1.000	0.900	0.867	0.900	1.000	1.000	0.999	0.997	**1.000**	0.947	0.912	0.915
SB	0.833	0.833	0.824	0.750	0.938	0.938	0.875	0.750	0.996	0.996	0.996	0.995	**0.882**	**0.882**	0.848	0.750
AF	1.000	0.769	0.800	0.571	0.769	0.769	0.615	0.923	1.000	0.996	0.998	0.989	**0.870**	0.769	0.696	0.706
ST	0.947	0.968	0.946	0.912	0.973	0.811	0.946	0.838	0.997	0.999	0.997	0.996	**0.960**	0.882	0.946	0.873

PPV positive predictive value. The bold values represent the best scores.

Ribiero A et al. Nature Comm 2020; 11:1760

Arrhythmia detection using AI in ECG

Automatic multilabel electrocardiogram diagnosis of heart rhythm or conduction abnormalities with deep learning: a cohort study

Hongling Zhu, Cheng Cheng*, Hang Yin, Xingyi Li, Ping Zuo, Jia Ding, Fan Lin, Jingyi Wang, Beitong Zhou, Yonge Li, Shouxing Hu, Yulong Xiong, Binran Wang, Guohua Wan, Xiaoyun Yang, Ye Yuan*

	Model AUC ROC (95% CI)	Model sensitivity (95% CI)	Model specificity (95% CI)	Model F1 score (95% CI)	Physicians' mean F1 score
Normal	1·000 (1·000–1·000)	1·000 (1·000–1·000)	1·000 (0·999–1·000)	0·998 (0·994–1·000)	0·834
Atrial flutter	0·993 (0·99–0·995)	0·898 (0·884–0·912)	0·992 (0·991–0·993)	0·880 (0·867–0·893)	0·836
Atrial fibrillation	0·991 (0·989–0·993)	0·873 (0·856–0·889)	0·985 (0·982–0·987)	0·863 (0·848–0·877)	0·839
Paroxysmal supraventricular tachycardia	0·982 (0·976–0·987)	0·895 (0·887–0·904)	0·999 (0·998–0·999)	0·931 (0·927–0·936)	0·808
Artificial atrial pacing rhythm	1·000 (0·999–1·000)	0·986 (0·972–1·000)	1·000 (1·000–1·000)	0·992 (0·983–1·000)	0·947
Artificial ventricular pacing rhythm	0·990 (0·988–0·991)	0·890 (0·880–0·900)	0·997 (0·996–0·997)	0·917 (0·909–0·924)	0·909
Mobitz type I second-degree atrioventricular block	1·000 (1·000–1·000)	0·988 (0·976–0·999)	1·000 (0·999–1·000)	0·989 (0·981–0·997)	0·952
Wolff-Parkinson-White syndrome type B	0·997 (0·995–0·999)	0·917 (0·899–0·935)	0·998 (0·997–0·999)	0·941 (0·931–0·951)	0·858
Wolff-Parkinson-White syndrome type A	1·000 (1·000–1·000)	0·991 (0·983–0·998)	0·997 (0·996–0·997)	0·972 (0·967–0·978)	0·891
Mean	0·995 (0·993–0·996)	0·937 (0·926–0·948)	0·996 (0·995–0·997)	0·943 (0·934–0·951)	0·875

Nine of the most common arrhythmias are shown here; results for other classes are shown in appendix 1 (p 9). AUC=area under the curve. ROC=receiver operating characteristic.

Table: **Performance summary of the deep learning model in arrhythmia diagnosis, and F1 scores for the deep learning model and physicians working in cardiology departments**

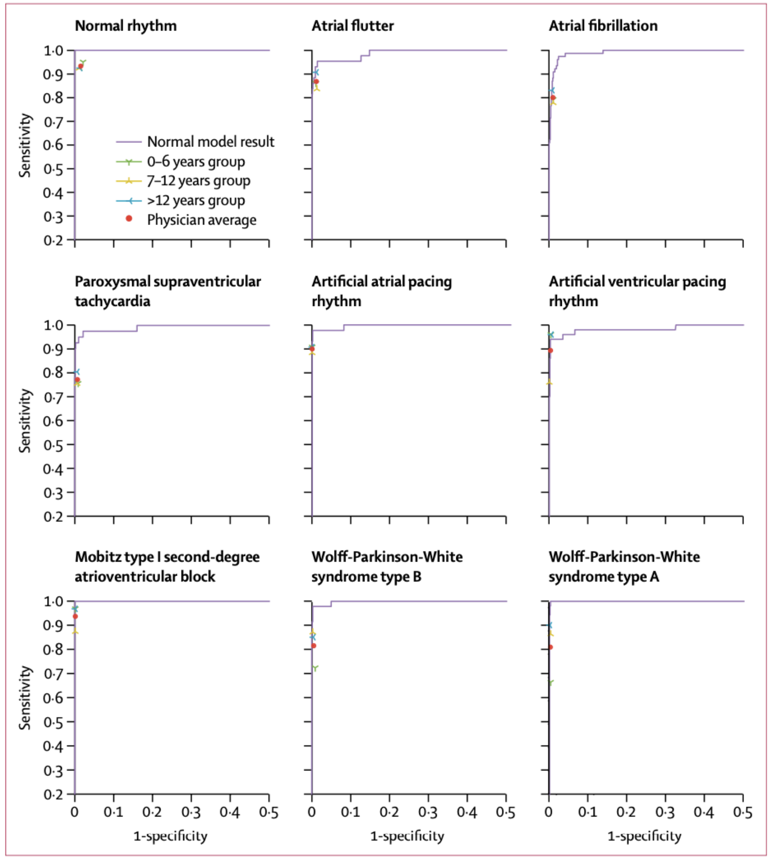


Figure 3: **ROC curves of prediction sensitivity of the deep learning model for nine of the included rhythm classes, compared with physicians**
ROC=receiver operating characteristic.

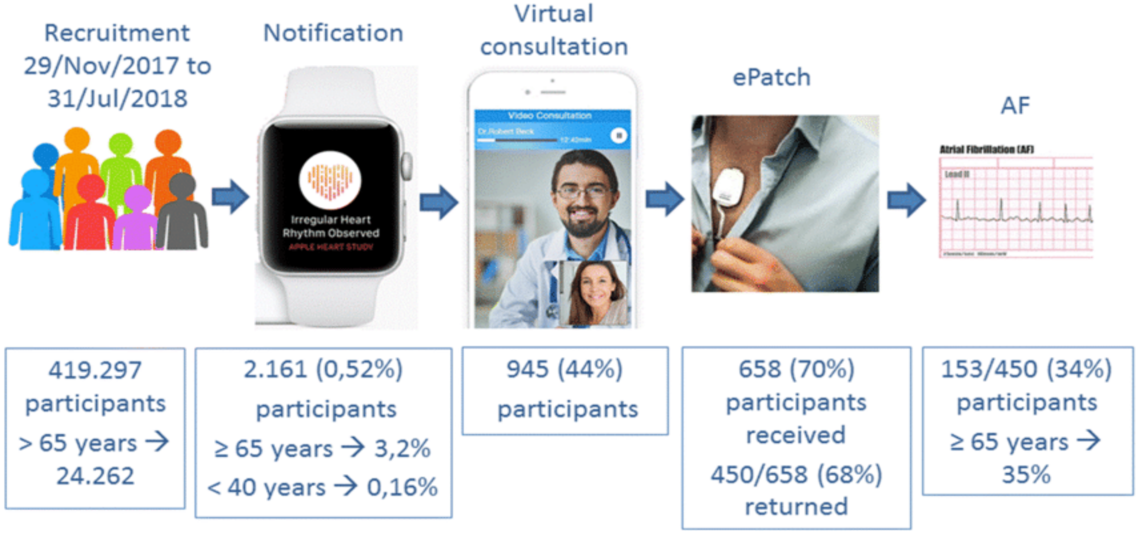
Zhu H et al. Lancet Digital Health 2020; 2: e348–57

Apple Heart Study

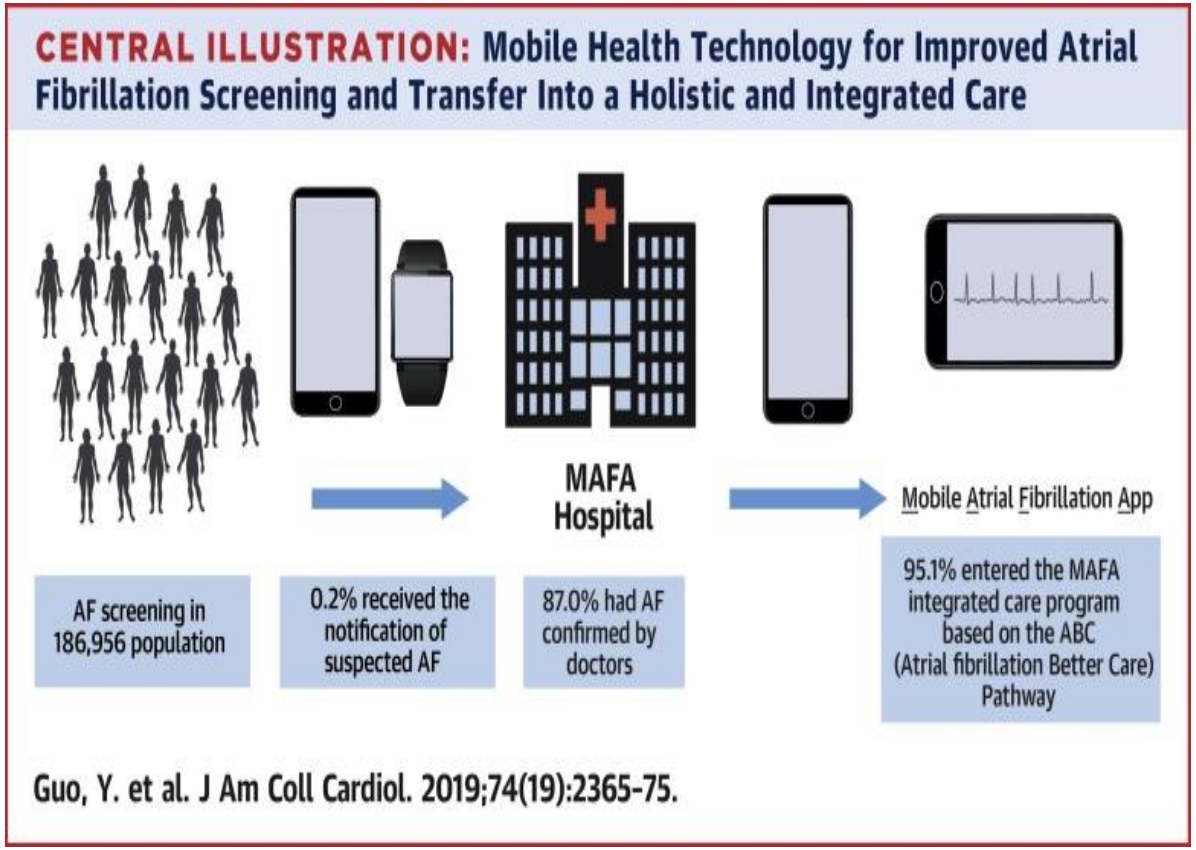

HEALTH NEWS

The new Apple Watch has a heart monitor and the FDA approves

Health apps can help patients take charge of their health, says the American Heart Association, which also suports the EKG app.



Huawei Heart Study



Arrhythmia detection using AI in ECG

TABLE 2 Selected Studies Using Artificial Intelligence Within Cardiology

First Author, Year	Purpose	Input	Sites	Patients	Studies	AUC	Strengths	Limitations	Other Performance Metrics
Guo et al, 2019[130]	Detection of atrial fibrillation on wearable smartwatch	PPG	[a]	187,912	—	—	+ Translation of 12-lead ECG model to popular consumer device	– High selection bias for patients with Apple Watch, MyChart, research compliance	87% of patients with suspected AF notification and follow-up had confirmed AF
Perez et al, 2019[131]	Detection of atrial fibrillation on wearable smartwatch	PPG	[a]	419,297	—	—	+ Large study with popular consumer device + Tackled implementation challenges of real-world population with low disease prevalence	– No follow-up to determine stroke benefit – Depended on participant adherence to follow-up measures, potentially introducing bias	0.5% of patients received irregular pulse notification and follow-up; 34% had confirmed AF
Lubitz et al, 2022[132]	Detection of atrial fibrillation on wearable smartwatch	PPG	[a]	455,699	—	—	+ Large study with popular consumer device + Included medical/social history data	– Detection during active motion remains significant challenge	1% of patients received irregular pulse notification and follow-up; 32% had confirmed AF

Elias P et al. J Am Coll Cardiol 2024;83:2472–2486

Prediction of paroxysmal AF in sinus rhythm

TABLE 2 Selected Studies Using Artificial Intelligence Within Cardiology

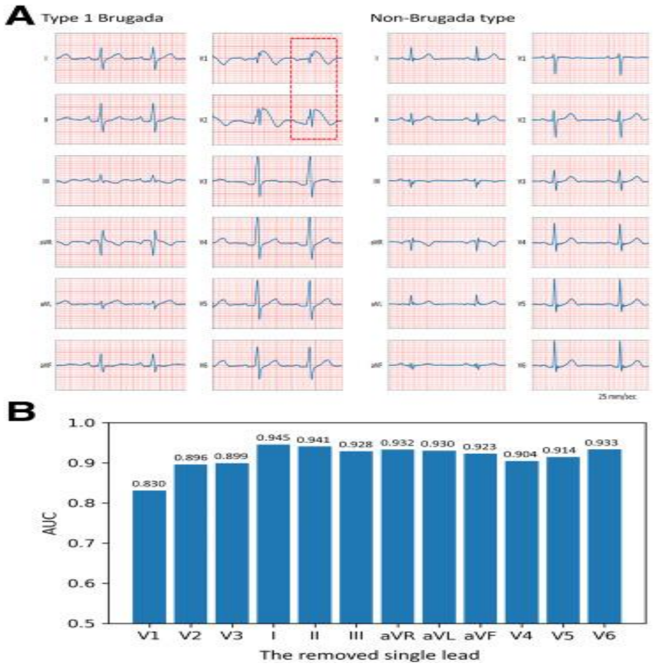
First Author, Year	Purpose	Input	Sites	Patients	Studies	AUC	Strengths	Limitations	Other Performance Metrics
Attia et al, 2019[14]	Identification of atrial fibrillation from ECG in normal sinus rhythm	12-lead ECG	1	180,922	649,931	0.87	+ First study to demonstrate novel pattern recognition achievable with deep learning	– Significant differences in age, comorbidities between 2 comparator groups means model can learn from confounders	AUC increased to 0.90 when ECG obtained within 30 d of atrial fibrillation ECG
Raghunath et al, 2021[13]	Identification of atrial fibrillation from ECG in normal sinus rhythm	12-lead ECG	1	430,000	1,600,000	0.85	+ Looked at number of preventable strokes in simulation	– Study population was 97% White – Single site with no external testing	Number needed to screen to find 1 new case of atrial fibrillation was 9. Deep learning outperformed the CHARGE-AF score (0.85 vs 0.77).

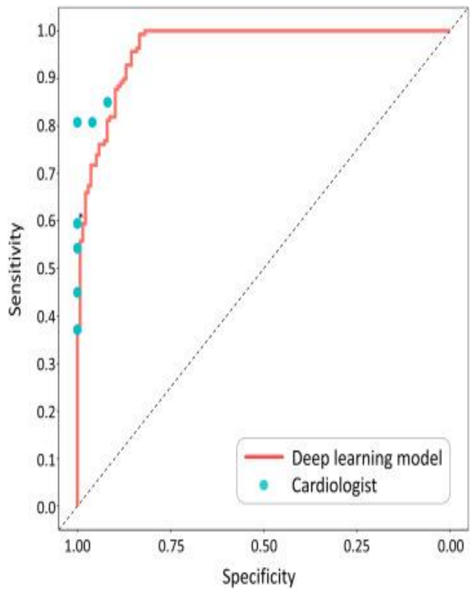
Elias P et al. J Am Coll Cardiol 2024;83:2472–2486

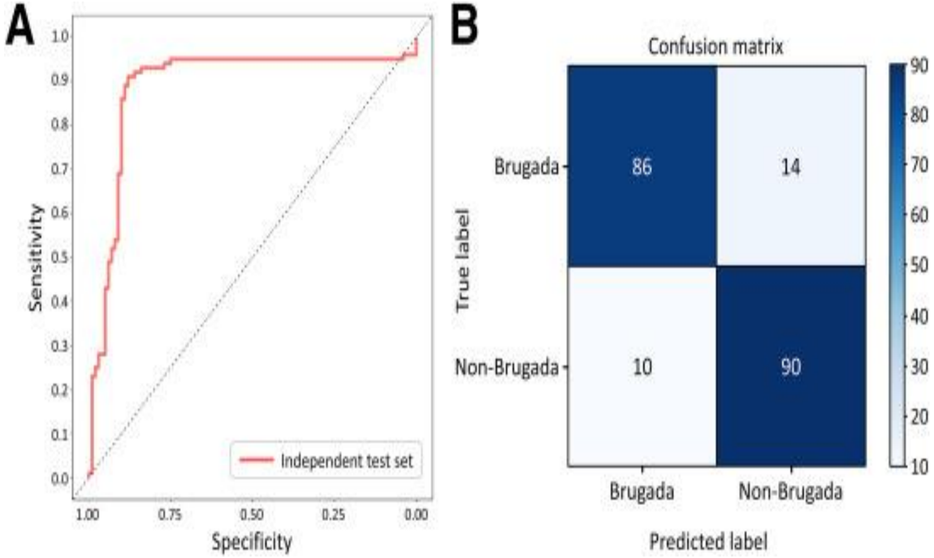
Diagnosis of arrhythmogenic syndromes

- AI has higher capability to detect channelopathies. The machine outperforms the human eye.

Deep learning enabled ECG model for detecting Brugada Syndrome



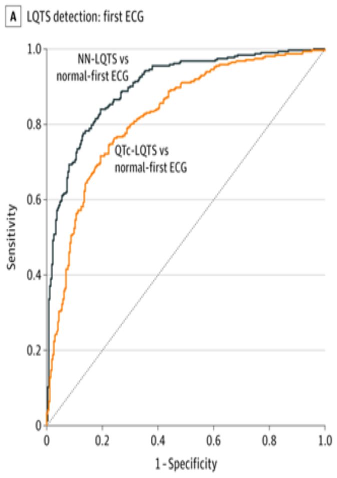




Liu C et al. Can J Cardiol. 2022 Feb;38(2):152-159.

Use of Artificial Intelligence and Deep Neural Networks in Evaluation of Patients With Electrocardiographically Concealed Long QT Syndrome From the Surface 12-Lead Electrocardiogram

AI ECG capable of distinguishing patients with ECG concealed long QT syndrome from those without long QT syndrome

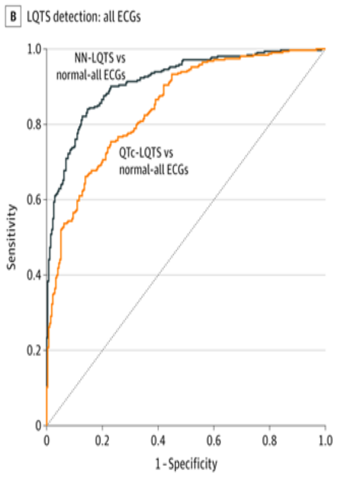


QTc-LQTS vs normal

	Estimated negative	Estimated positive
Real negative	213	61
Real positive	80	233

NN-LQTS vs normal

	Estimated negative	Estimated positive
Real negative	221	53
Real positive	50	263

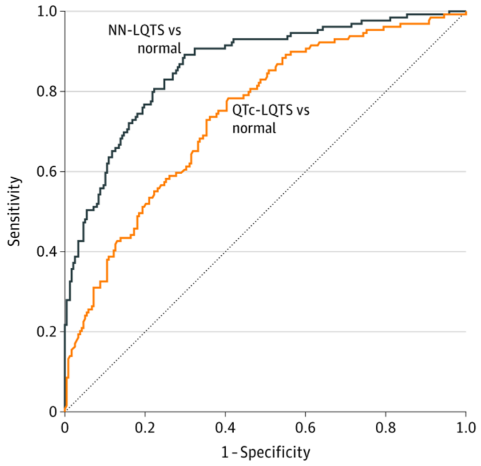


QTc-LQTS vs normal

	Estimated negative	Estimated positive
Real negative	211	63
Real positive	77	236

NN-LQTS vs normal

	Estimated negative	Estimated positive
Real negative	234	40
Real positive	50	263

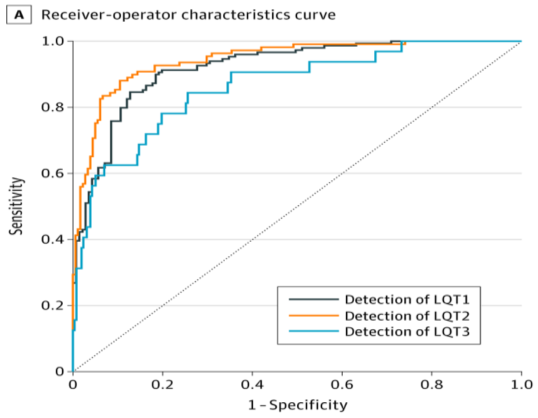


QTc-LQTS vs normal

	Estimated negative	Estimated positive
Real negative	154	84
Real positive	35	94

NN-LQTS vs normal

	Estimated negative	Estimated positive
Real negative	185	53
Real positive	25	104



B Confusion matrix

	Predicted LQT1	Predicted LQT2	Predicted LQT3	Total	Accuracy, %
Actual LQT1	130	10	9	149	87.2
Actual LQT2	15	92	2	109	84.4
Actual LQT3	10	6	16	32	50.0
Total	155	108	27	264	

Bos JM et al. JAMA Cardiol. 2021;6(5)

Prediction of structural heart disease from AI-ECG

- 1. LV systolic dysfunction (low LVEF)
- 2. Cardiomyopathies
- 3. Aortic stenosis
- 4. Cardiac amyloidosis

Prediction of structural heart disease from AI-ECG

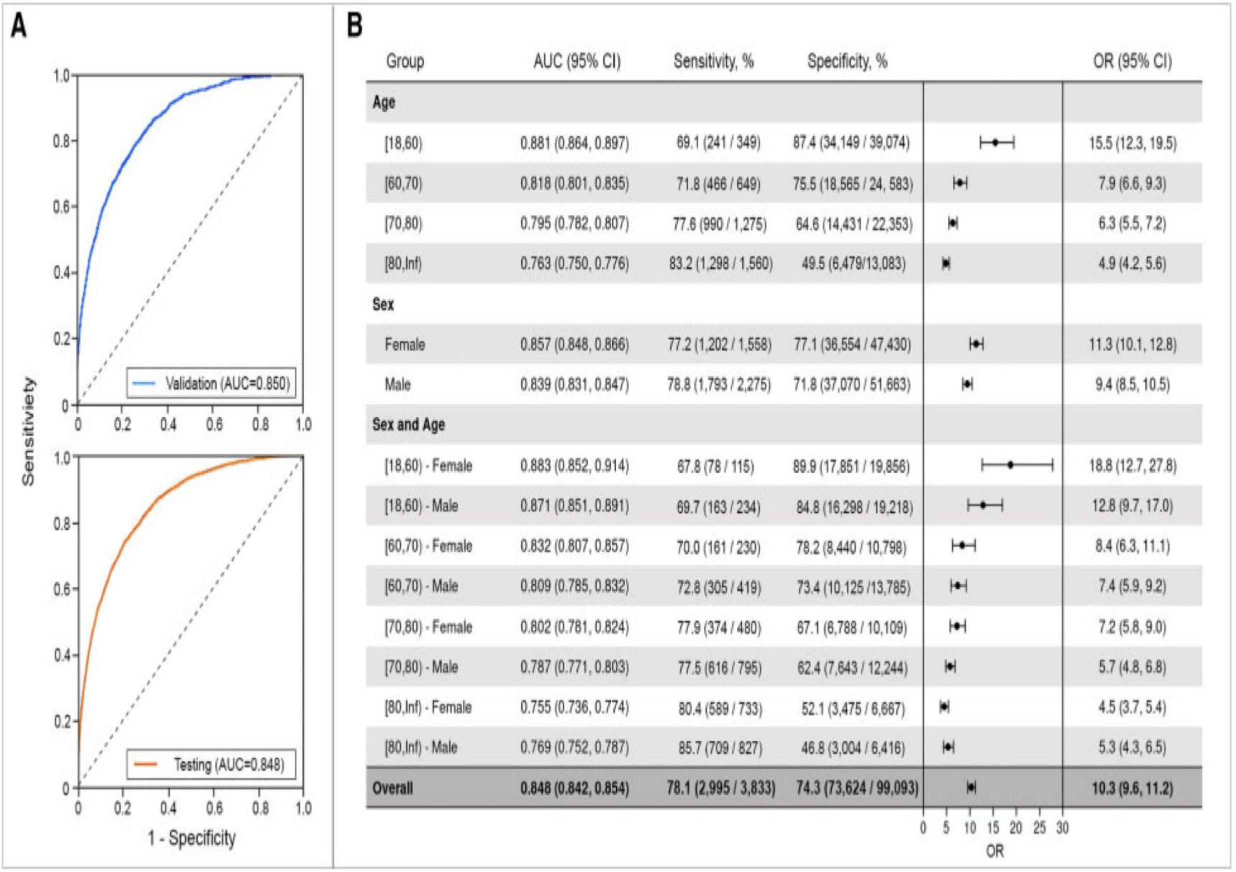
TABLE 2 Selected Studies Using Artificial Intelligence Within Cardiology

First Author, Year	Purpose	Input	Sites	Patients	Studies	AUC	Strengths	Limitations	Other Performance Metrics
								from confounders	
Attia et al, 2019[26]	Screening for asymptomatic LV dysfunction (LVEF ≤35%)	12-lead ECG	1	97,829	97,829	0.93	+ Large population with ECG and TTE done within 2 weeks of one another	– No race/ethnicity data, likely limited population diversity	Positive AI screen without ventricular dysfunction at 4× risk of developing LV dysfunction
Ko et al, 2020[35]	Identification of HCM	12-lead ECG	1	67,001	67,001	0.96	+ Largest HCM study population + ECGs from over 30 y	– HCM prevalence in data set was ~4%, but real-world population of interest likely 10× lower.	AUC 0.95 within subgroup of patients with LVH
Cohen-Shelly et al, 2021[42]	Detection of AS	12-lead ECG	3	258,607	258,607	0.85	+ 3 tertiary referral centers in geographically distinct locations	– Population was 88% Caucasian – No external test set	False-positives had twice the risk for developing moderate-severe AS in 15 y
Elias et al, 2022[43]	Detection of AS, AR, and MR	12-lead ECG	4	77,163	260,811	0.84	+ Tested and validated at 4 hospitals, mix of academic/ community	– Performance dropped by 9% in hospital not included in training data	AUC for AS; AUC for AR 0.77 and MR 0.83
Sangha et al, 2023[28]	Screening for asymptomatic LV dysfunction (LVEF ≤40%)	12-lead ECG	7	116,210	385,601	0.91	+ Validated externally and on ECG images that can be uploaded to web-app	– Trained on patients with ECG /echo, who differ from intended screening population.	AUC range 0.88 to 0.95 across external sets. Positive screen with >27-fold higher odds of LV dysfunction

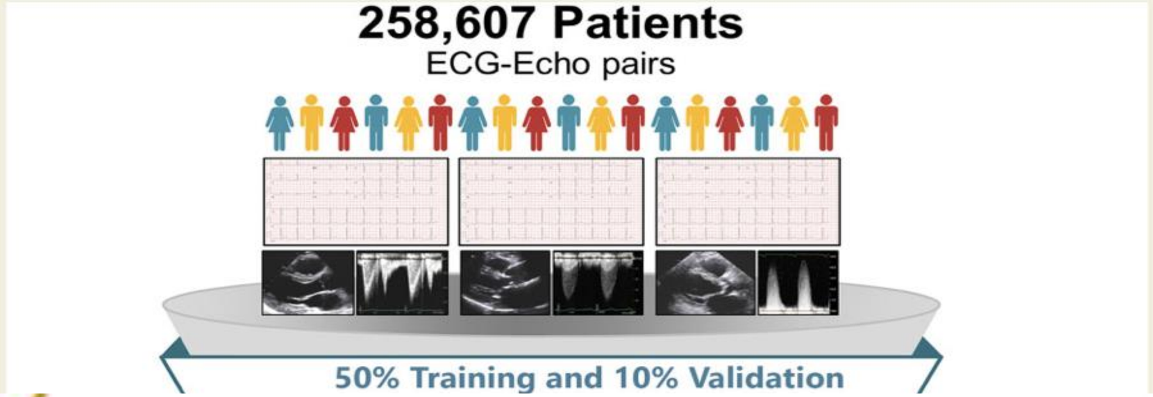
Elias P et al. J Am Coll Cardiol 2024;83:2472–2486

Electrocardiogram screening for aortic valve stenosis using artificial intelligence

Michal Cohen-Shelly [1], Zachi I. Attia [1], Paul A. Friedman[1], Saki Ito[1], Benjamin A. Essayagh [1], Wei-Yin Ko[1], Dennis H. Murphree [1], Hector I. Michelena [1], Maurice Enriquez-Sarano[1], Rickey E. Carter [2], Patrick W. Johnson [2], Peter A. Noseworthy[1], Francisco Lopez-Jimenez [1], and Jae K. Oh[1]*



Group	AUC (95% CI)	Sensitivity, %	Specificity, %	OR (95% CI)
Age				
[18,60)	0.881 (0.864, 0.897)	69.1 (241 / 349)	87.4 (34,149 / 39,074)	15.5 (12.3, 19.5)
[60,70)	0.818 (0.801, 0.835)	71.8 (466 / 649)	75.5 (18,565 / 24, 583)	7.9 (6.6, 9.3)
[70,80)	0.795 (0.782, 0.807)	77.6 (990 / 1,275)	64.6 (14,431 / 22,353)	6.3 (5.5, 7.2)
[80,Inf)	0.763 (0.750, 0.776)	83.2 (1,298 / 1,560)	49.5 (6,479/13,083)	4.9 (4.2, 5.6)
Sex				
Female	0.857 (0.848, 0.866)	77.2 (1,202 / 1,558)	77.1 (36,554 / 47,430)	11.3 (10.1, 12.8)
Male	0.839 (0.831, 0.847)	78.8 (1,793 / 2,275)	71.8 (37,070 / 51,663)	9.4 (8.5, 10.5)
Sex and Age				
[18,60) - Female	0.883 (0.852, 0.914)	67.8 (78 / 115)	89.9 (17,851 / 19,856)	18.8 (12.7, 27.8)
[18,60) - Male	0.871 (0.851, 0.891)	69.7 (163 / 234)	84.8 (16,298 / 19,218)	12.8 (9.7, 17.0)
[60,70) - Female	0.832 (0.807, 0.857)	70.0 (161 / 230)	78.2 (8,440 / 10,798)	8.4 (6.3, 11.1)
[60,70) - Male	0.809 (0.785, 0.832)	72.8 (305 / 419)	73.4 (10,125 /13,785)	7.4 (5.9, 9.2)
[70,80) - Female	0.802 (0.781, 0.824)	77.9 (374 / 480)	67.1 (6,788 / 10,109)	7.2 (5.8, 9.0)
[70,80) - Male	0.787 (0.771, 0.803)	77.5 (616 / 795)	62.4 (7,643 / 12,244)	5.7 (4.8, 6.8)
[80,Inf) - Female	0.755 (0.736, 0.774)	80.4 (589 / 733)	52.1 (3,475 / 6,667)	4.5 (3.7, 5.4)
[80,Inf) - Male	0.769 (0.752, 0.787)	85.7 (709 / 827)	46.8 (3,004 / 6,416)	5.3 (4.3, 6.5)
Overall	**0.848 (0.842, 0.854)**	**78.1 (2,995 / 3,833)**	**74.3 (73,624 / 99,093)**	**10.3 (9.6, 11.2)**

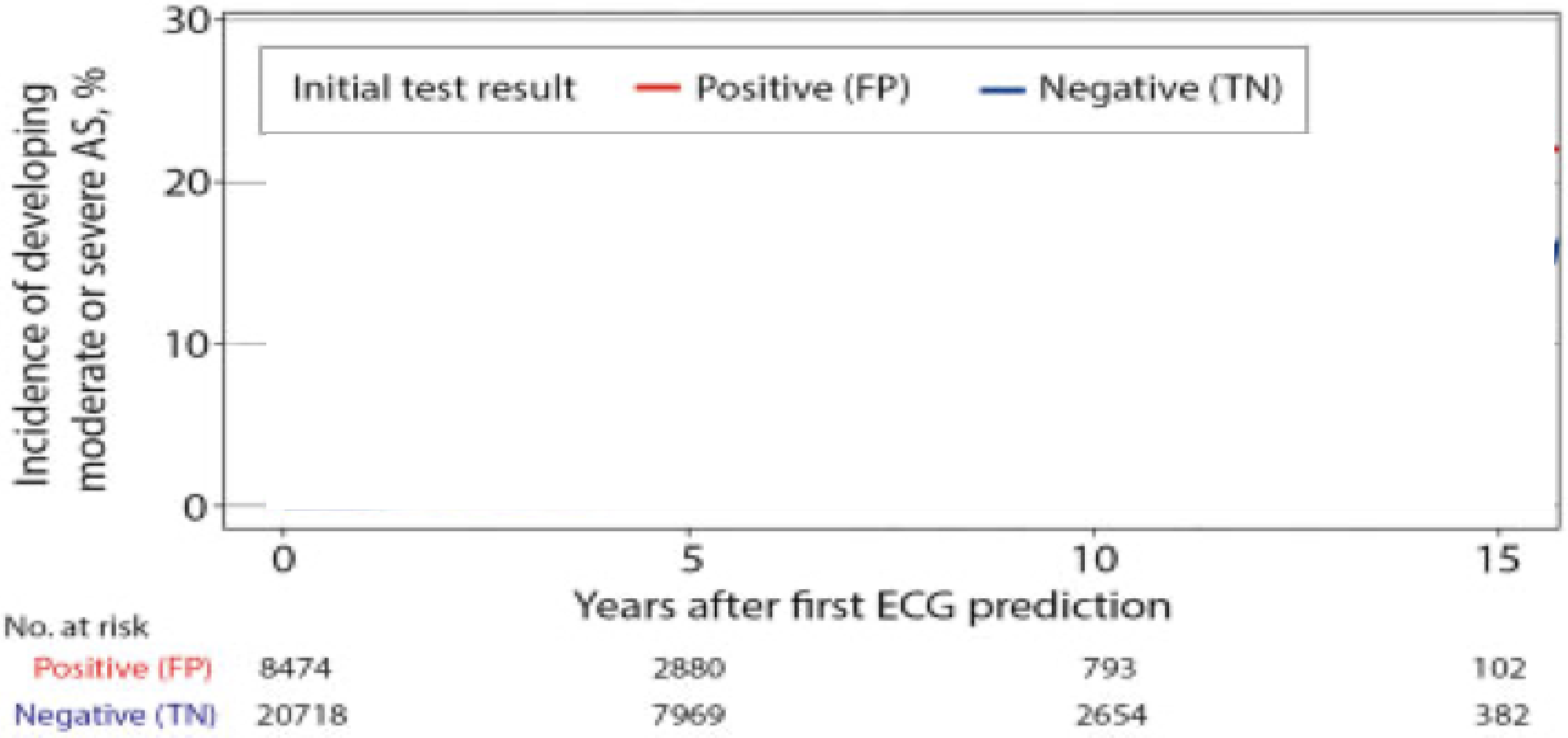


Model	AUC	Sensitivity	Specificity
1	0.85	78.0%	74.0%
2	0.87	78.0%	79.8%
3	0.90	75.0%	88.0%

1: ECG only
2: ECG + Age & Sex
3: Model 2 for non-hypertensive patients

Cohen-Shelly M et al. European Heart Journal 2020; 42: 2885–2896

Prediction of aortic stenosis from AI-ECG



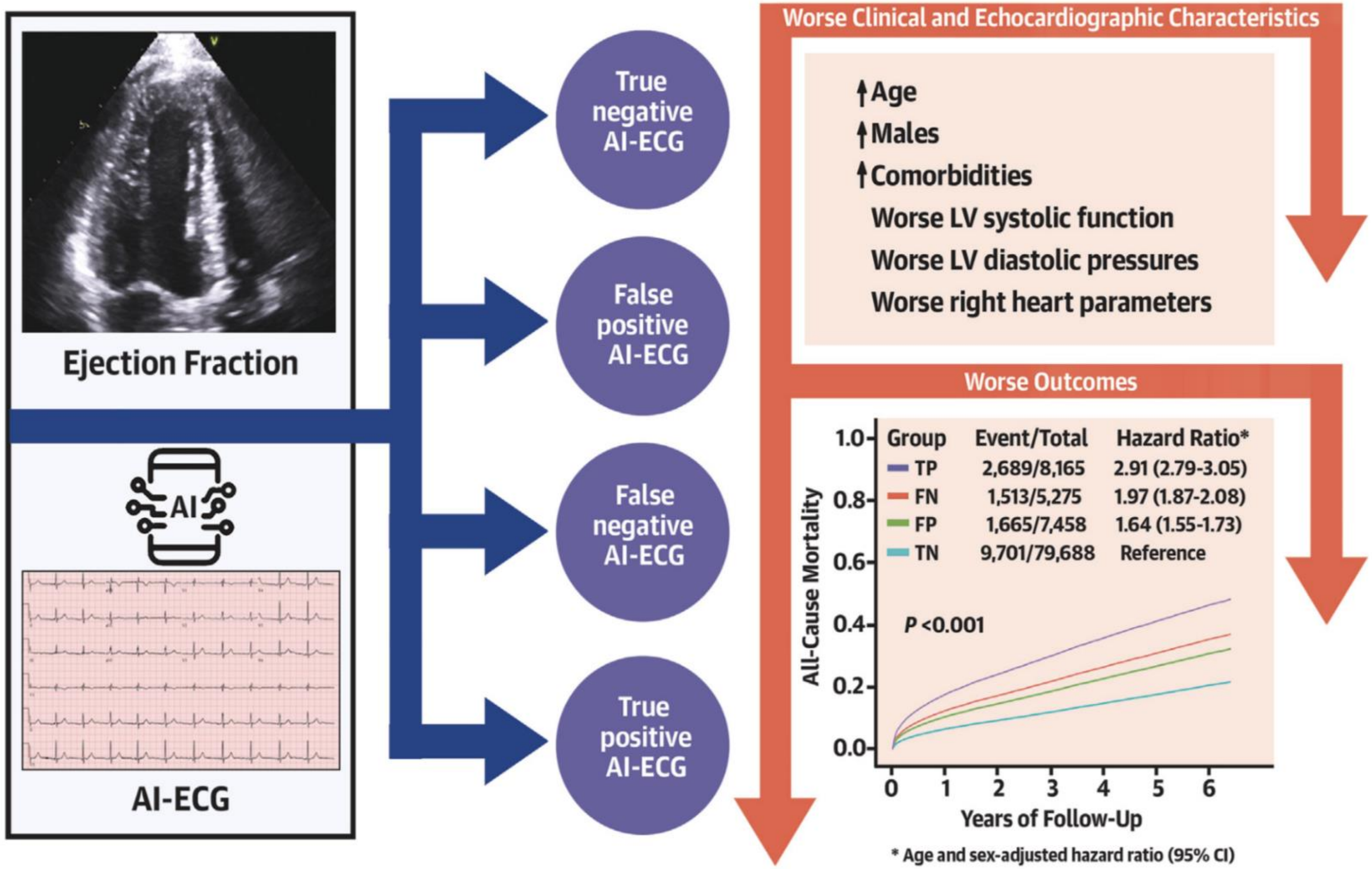
Cohen-Shelly M et al. European Heart Journal 2020; 42: 2885–2896

Artificial Intelligence–Enhanced Electrocardiography Identifies Patients With Normal Ejection Fraction at Risk of Worse Outcomes

Jwan A. Naser, MBBS,[a] Eunjung Lee, PhD,[a] Francisco Lopez-Jimenez, MD, MBA,[a] Peter A. Noseworthy, MD,[a] Omar S. Latif, MD,[b] Paul A. Friedman, MD,[a] Grace Lin, MD, MBA,[a] Jae K. Oh, MD,[a] Christopher G. Scott, MS,[c] Sorin V. Pislaru, MD, PhD,[a] Zachi I. Attia, PhD,[a] Patricia A. Pellikka, MD[a]

- 100,586 patients (median age 63 years; 45.5% females)
- False Positive ECGs (FPs) had more echocardiographic abnormalities than True Negative (TN) but less than False Negative (FN) or True Positive (TP) patients.
- An echocardiographic abnormality was present in 97% of FPs.

CENTRAL ILLUSTRATION Artificial Intelligence-Enhanced Electrocardiography Identifies Patients With Normal Ejection Fraction at Risk of Worse Outcomes



Naser JA, et al. JACC Adv.. 2024;■(■):101179.

The artificial intelligence (AI)-based ECG-stratified patients with normal ejection fraction (EF) into true negatives (TN) and false positives (FP) and patients with reduced EF <50% as true positives (TP) and false negatives (FN). Patients who are abnormal by the AI-ECG (TP, FP) had worse clinical and echocardiographic characteristics and outcomes compared to their counterparts with normal AI-ECG (FN, TN, respectively).

Naser J et al. JACC Adv. 2024;101179

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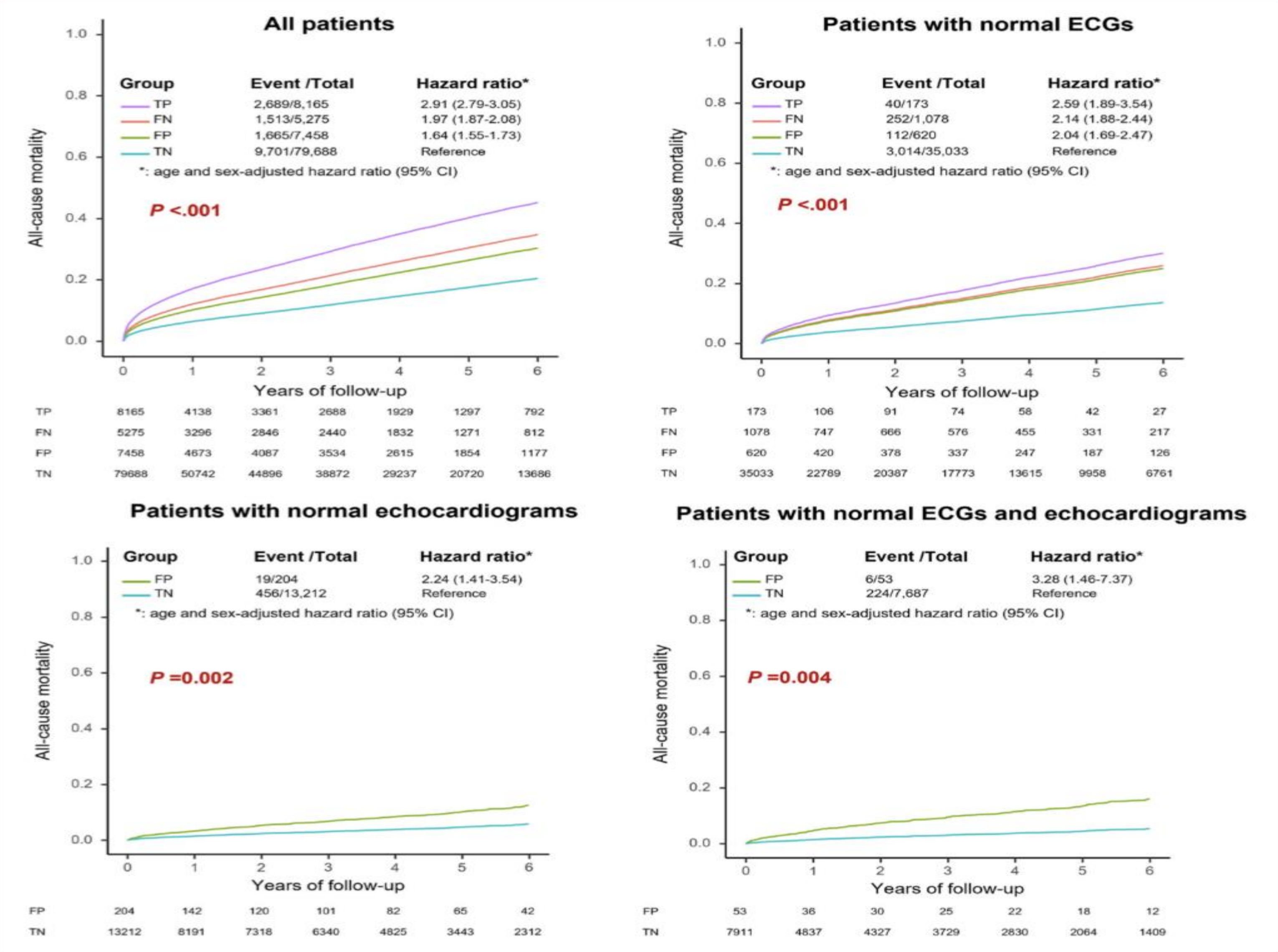
- Over median 2.7 years, FPs had increased mortality risk (age and sex-adjusted HR: 1.64 [95% CI: 1.55-1.73]) vs TN.

- Age and sex-adjusted mortality was higher in FP with abnormal echocardiography than FP with normal echocardiography.

FIGURE 2 Age and Sex-Adjusted Mortality Rates in the Different AI-ECG Groups

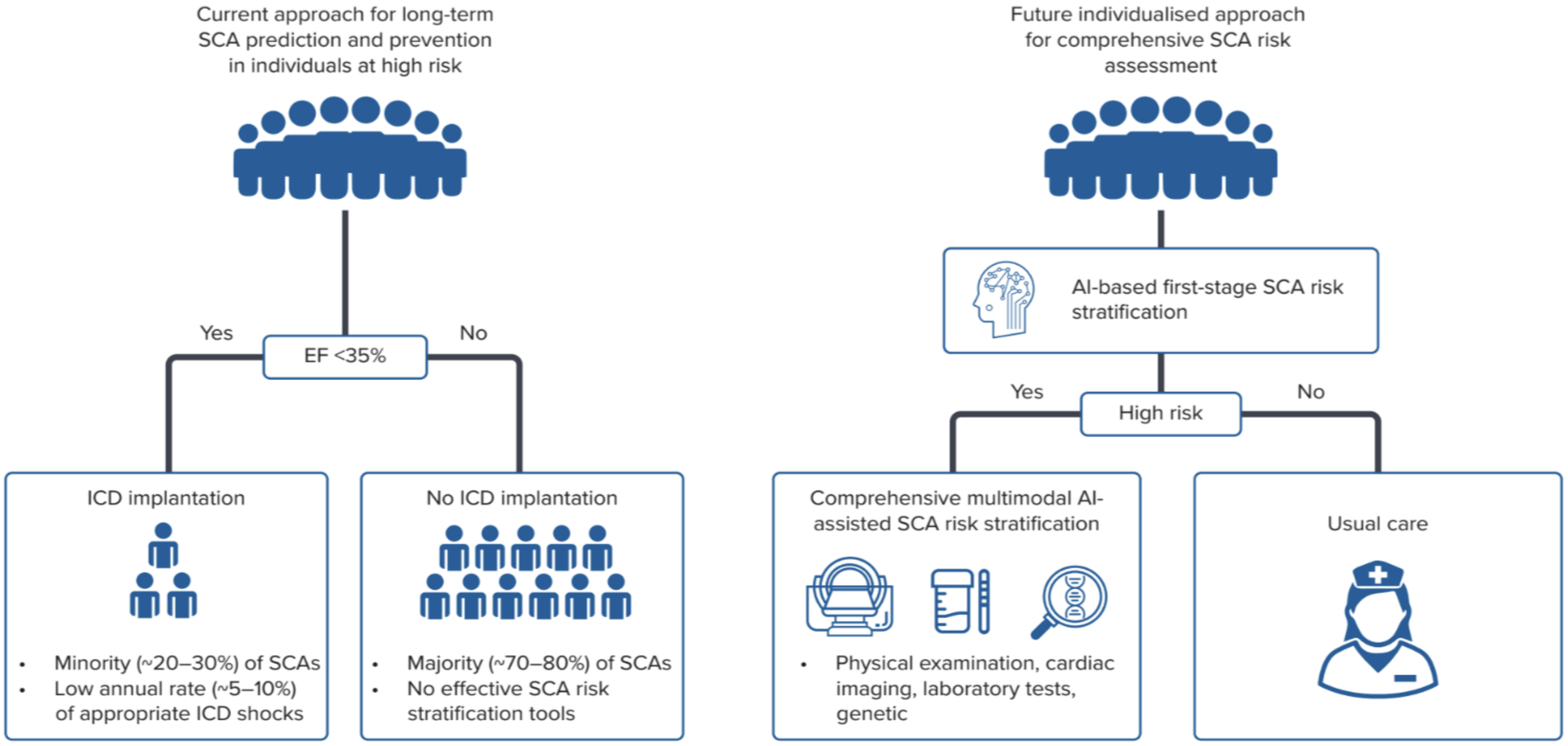


Comparison of all-cause mortality between the AI ECG groups is shown in the overall cohort (left top panel), in patients with normal ECG (right top panel), in patients without cardiomyopathy and with normal echocardiograms (left bottom panel), and in patients without cardiomyopathy and normal echocardiograms and ECG (right bottom panel). The AI-ECG groups included false positives (FP), true negatives (TN), false negatives (FN), and true positives (TP). Age- and sex-adjusted hazard ratios and 95% confidence intervals are shown.

Naser J et al. JACC Adv. 2024;101179

AI in Ventricular Arrhythmias and Sudden Cardiac Death

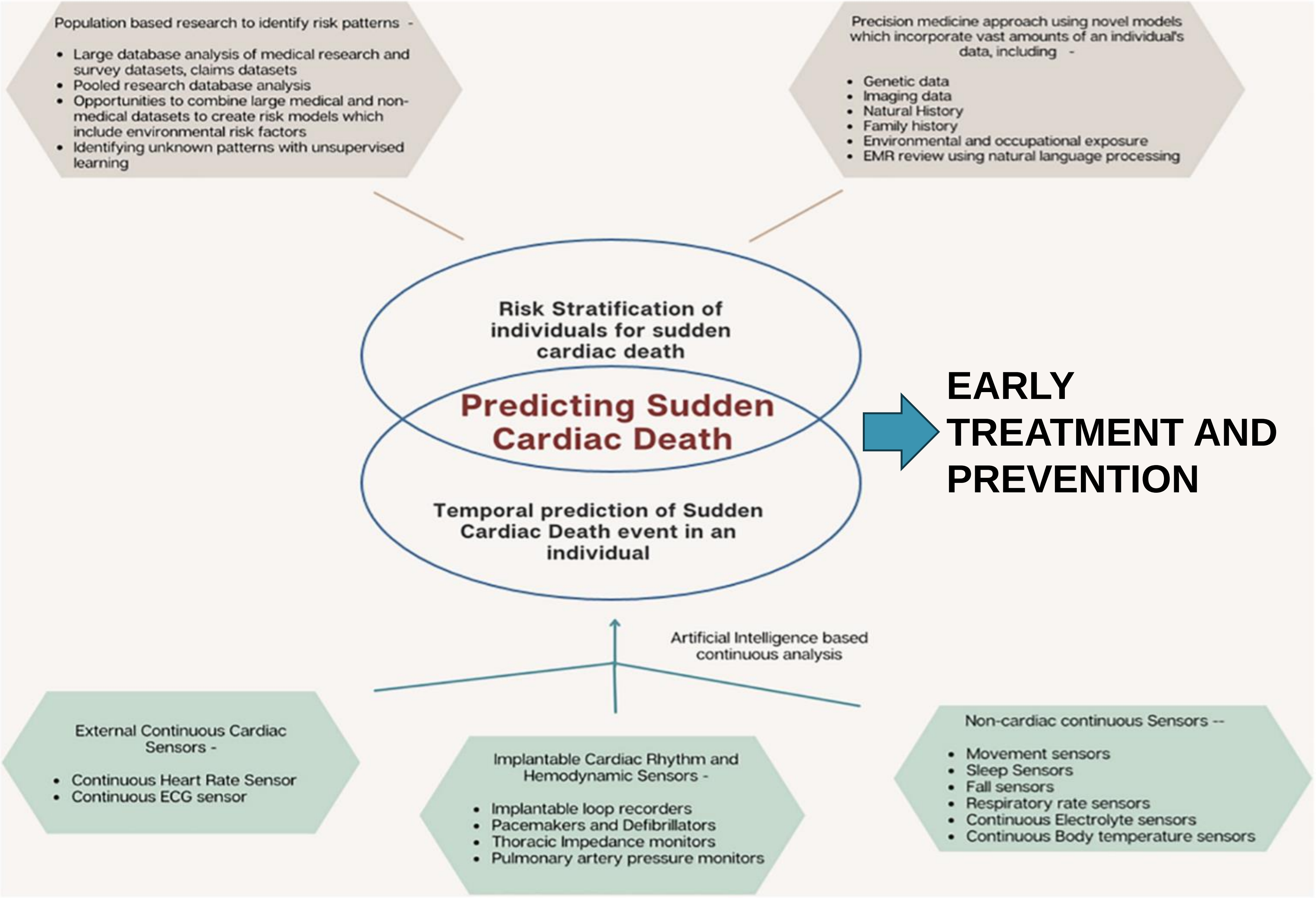
Figure 1: Current Approach and Potential Future Perspectives in Long-term Sudden Cardiac Arrest Prediction



AI = artificial intelligence; EF = ejection fraction; SCA = sudden cardiac arrest.

Kabra et al. Cardiovascular Digital Health Journal 2022;3:263–275

AI Model for Prediction of Sudden Cardiac Death



EARLY TREATMENT AND PREVENTION

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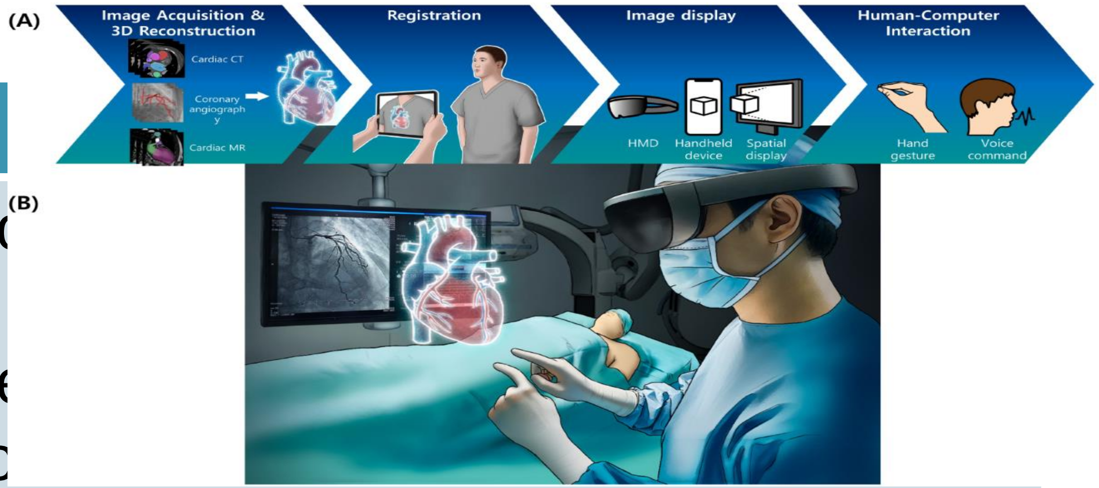
AI capabilities in Electrophysiology Procedures

Pre-procedural	Planning for ablatio Risk stratification Identification of site Prediction of respo
Intra-procedural	Extended reality he procedures Incorporation of int identify rotor target Localization of PVC
Post-procedural	Prediction of respo



AI capabilities in Cardiac Implantable Electronic Devices (Pacemakers, ICDs, CRTs)

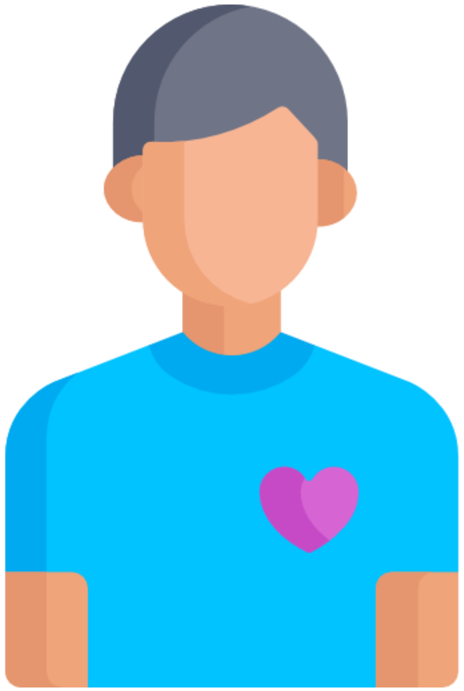
Pacemakers	Detection of arrhythmias (AF, VT, etc) Automatic programmability Smart algorithms
ICDs	Shock algorithms Prediction of (impending) ICD shocks, electrical storm Heart failure monitoring
CRTs	Optimization algorithms Prediction of CRT response

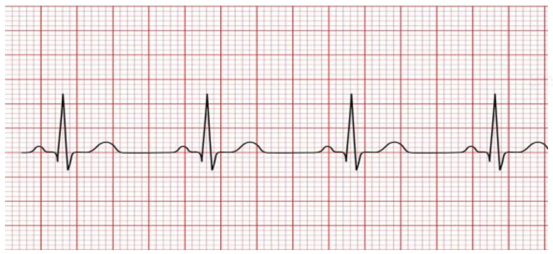
A DIGITAL REVOLUTION THAT WILL CHANGE THE LANDSCAPE OF CARDIOLOGY AND ELECTROPHYSIOLOGY

WE MUST EMBRACE THE PARADIGM SHIFT TOWARD AI

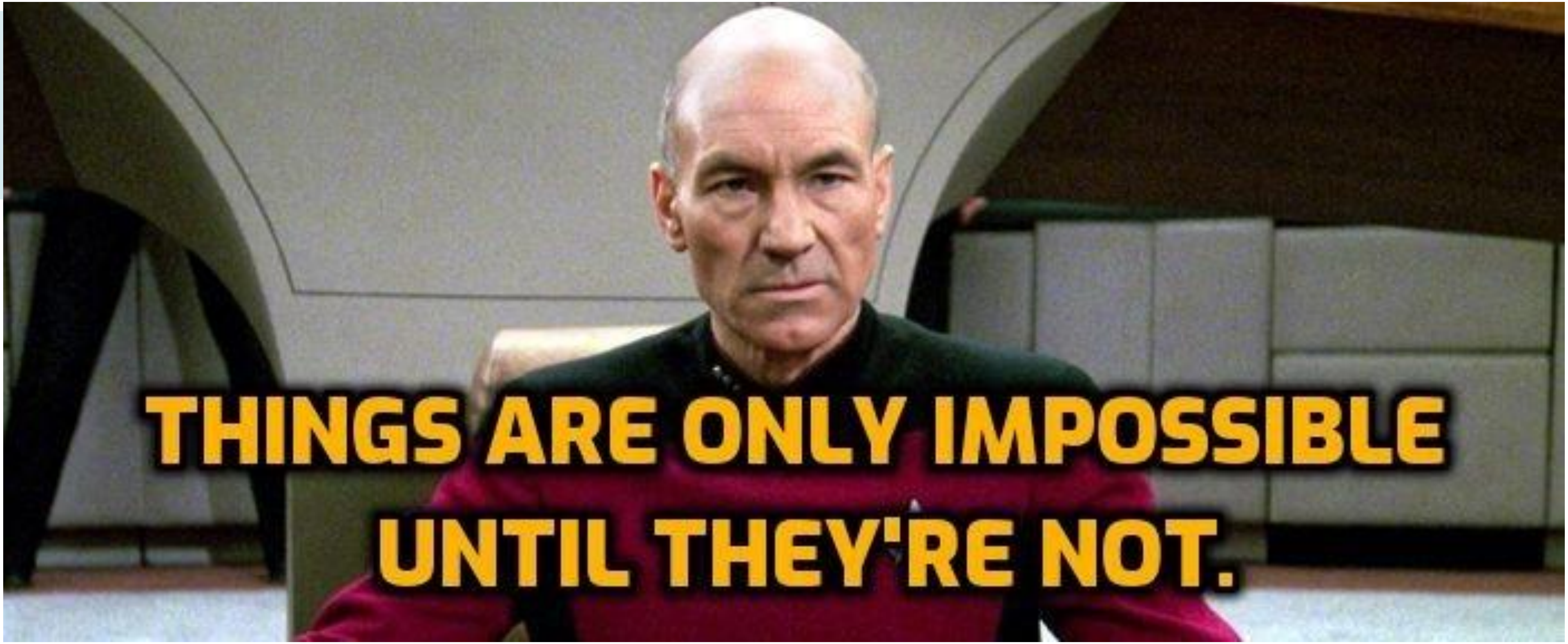
OPPORTUNITY FOR PERSONALIZED PRECISION MEDICINE

Future Outlook

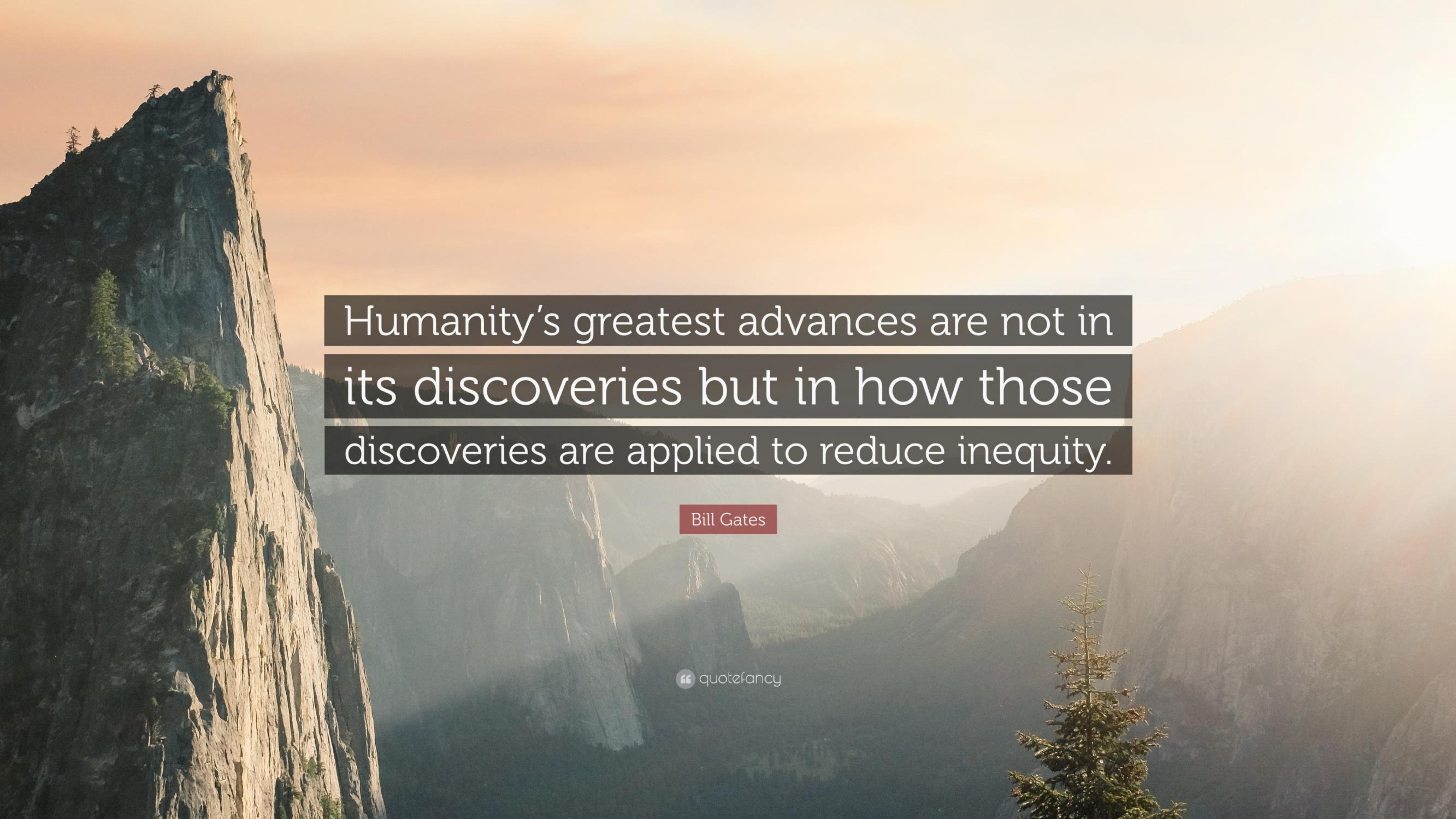




Diagnosis
Risk of heart disease
Risk of future heart attack
Probability of sudden death
Risk of heart failure
Metabolic parameters
Lifespan
Etc. etc.



THANK YOU AND GOOD DAY.


Humanity's greatest advances are not in its discoveries but in how those discoveries are applied to reduce inequity.
Bill Gates
quotefancy

Gaps and Challenges

Table 1 Important challenges/obstacles to translating artificial intelligence to clinical practice and suggestions for overcoming them

Challenges and obstacles	Potential approaches
1. Lack of transparency (black box analyses) inhibits clinician uptake	Correlation analyses can sometimes help improve transparency. Use of new approaches, such as gradient-weighted class activation mapping, can help provide a level of interpretability.
2. Lack of validation and reproducibility in independent data sets	As the main reason behind this challenge is lack of access to independent data sets, any approaches that facilitate consistent data sharing would help alleviate the problem. For example, journals could require data be made public and provide a unified service that is HIPAA compliant and gives authorized users access.
3. Implementation in the EHR may be inhibited by regulatory requirements for clinical use	FDA review and advances may facilitate approval steps.
4. Need for strong technical teams, including data scientists, computer scientists, analysts; attracting skilled personnel to academics and medicine can be difficult, as industry offers higher salaries	Increase training pipelines. Provide institutional incentives for multidisciplinary approaches. Create and facilitate access to AI consulting services within each institution. Incorporate AI in medical training.
5. Need for large, harmonized quality data sets with representation of normal and abnormal examples and representation of data from diverse populations to avoid bias; HIPAA and need to preserve patient privacy can inhibit availability of large data sets for development	FDA National Evaluation System for health technology initiative – aims to establish accessible data networks, including device registries, EHR, claims databases, and patient-generated health data.

AI = artificial intelligence; EHR = electronic health records.

Kabra et al. Cardiovascular Digital Health Journal 2022;3:263–275