Can Technology Impact the Quality of Care?

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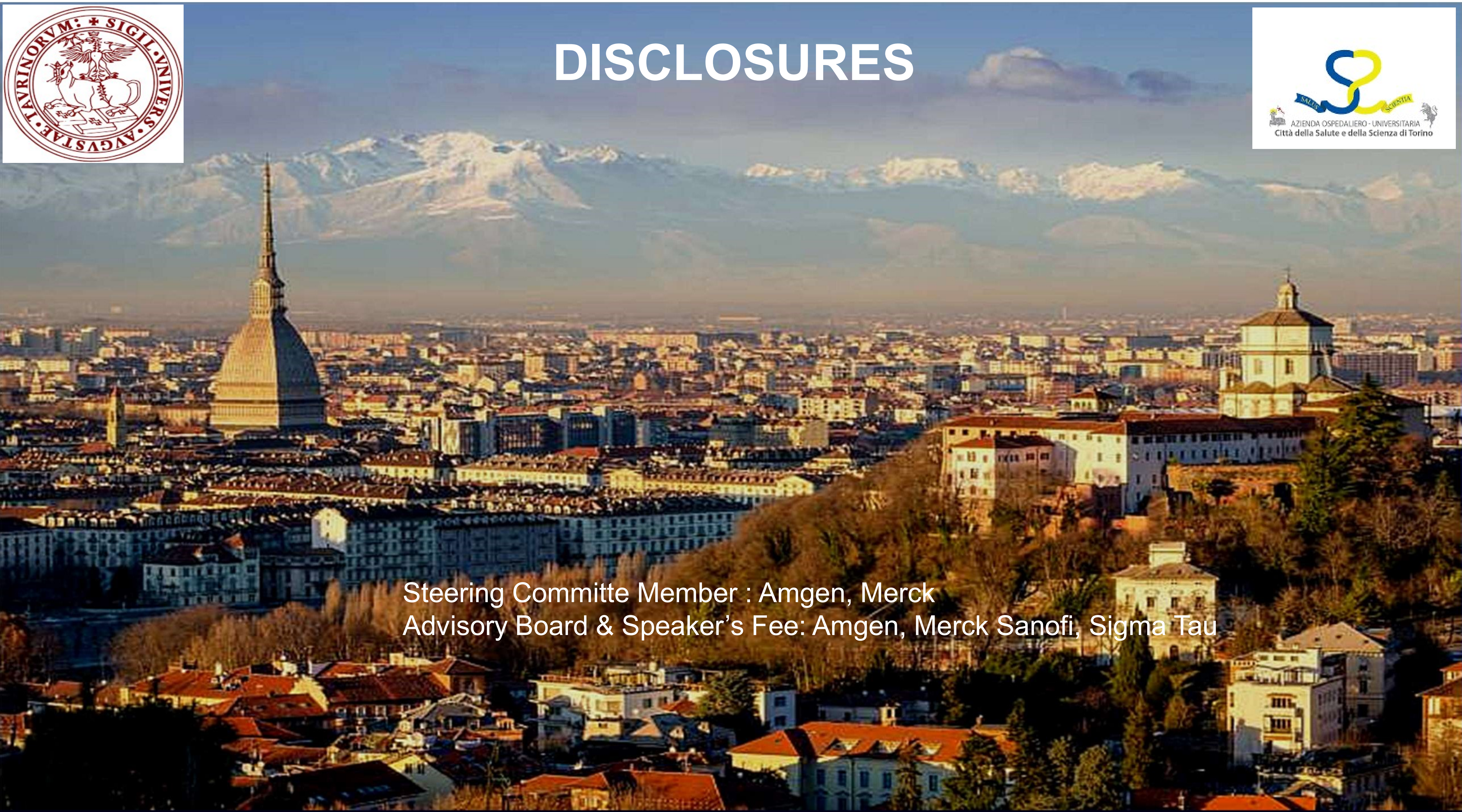
DISCLOSURES



Steering Committe Member : Amgen, Merck
Advisory Board & Speaker’s Fee: Amgen, Merck Sanofi, Sigma Tau

WHAT'S ON THE MENU?

1. Use of smart devices for diagnosis
2. Use of smart devices for clinical trials /registries
3. Use of Big data: Artificial Intelligence
4. AI: Machine Learning
5. AI & Modelling

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Can they save you from Sudden Cardiac Death ?

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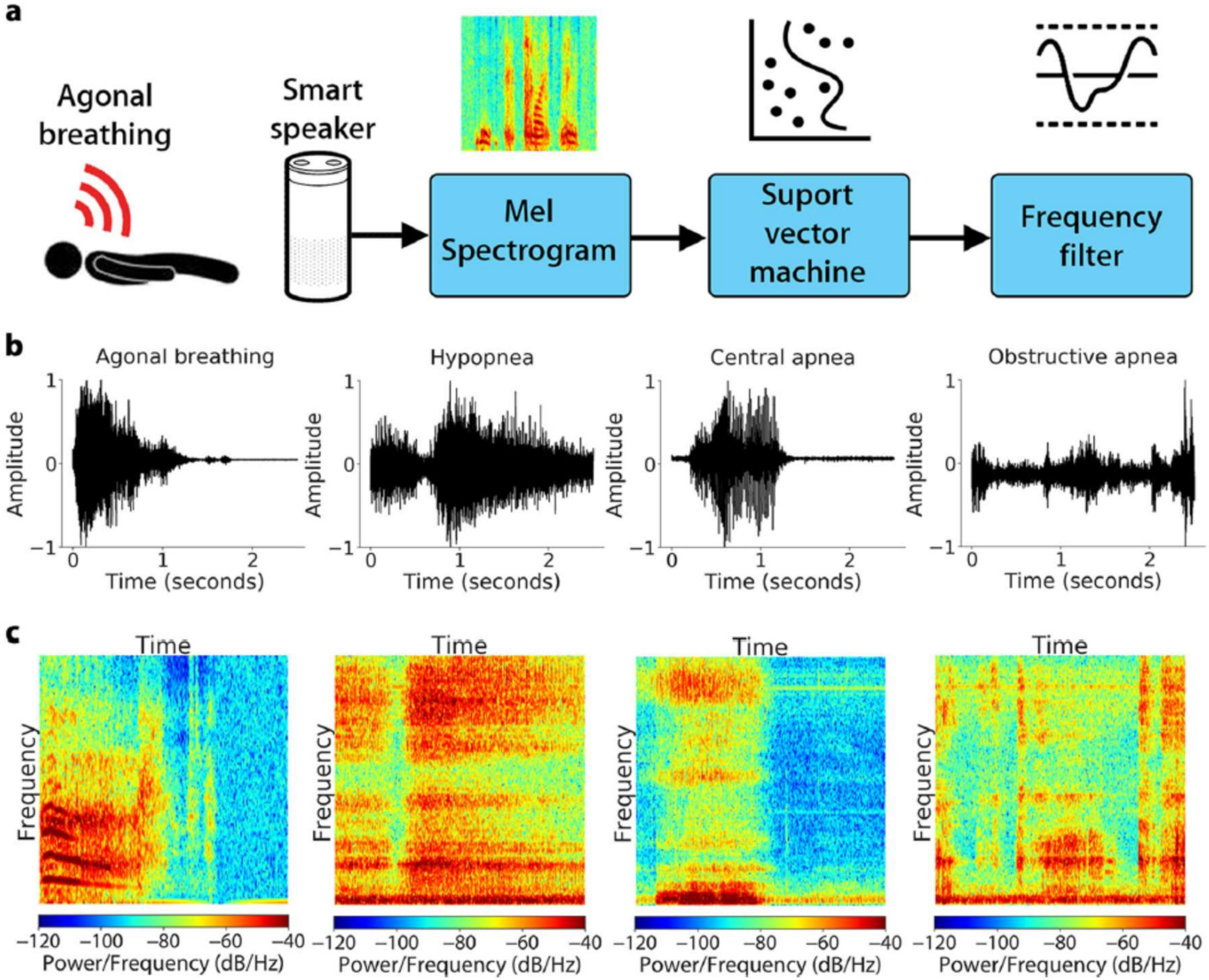
www.nature.com/npjdigitalmed

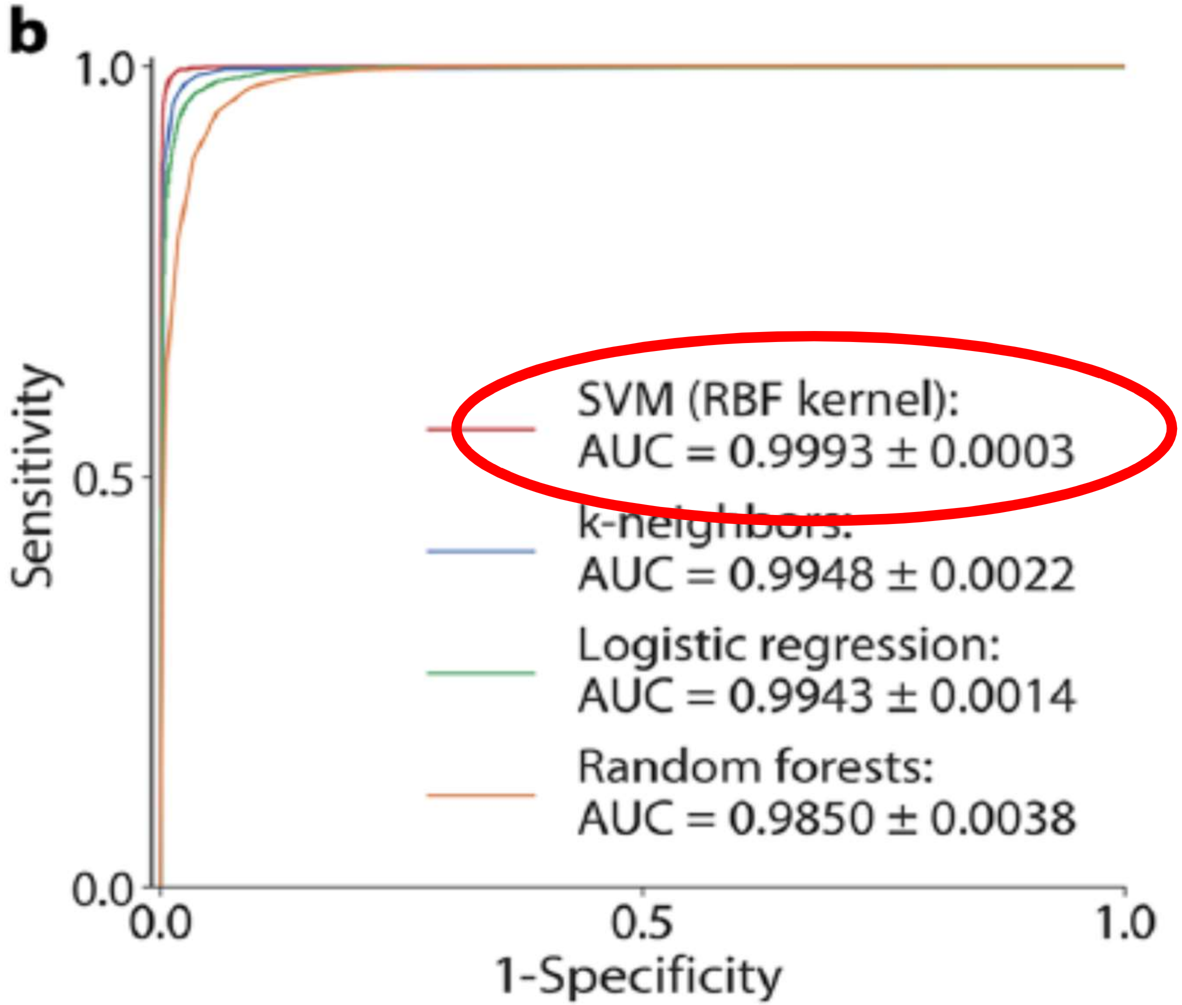
ARTICLE OPEN

Contactless cardiac arrest detection using smart devices

Justin Chan[1], Thomas Rea[2,3], Shyamnath Gollakota[1] and Jacob E. Sunshine[4]


a
Agonal breathing
Smart speaker
Mel Spectrogram
Suport vector machine
Frequency filter
b
Agonal breathing
Hypopnea
Central apnea
Obstructive apnea
Amplitude
Time (seconds)
c
Time
Frequency
Power/Frequency (dB/Hz)

Can the system be accurate ?



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Results of a Large-scale, App-based Study to Identify Atrial Fibrillation Using a Smartwatch:

The Apple Heart Study

Mintu Turakhia MD MAS and Marco Perez MD
on behalf of the Apple Heart Study Investigators

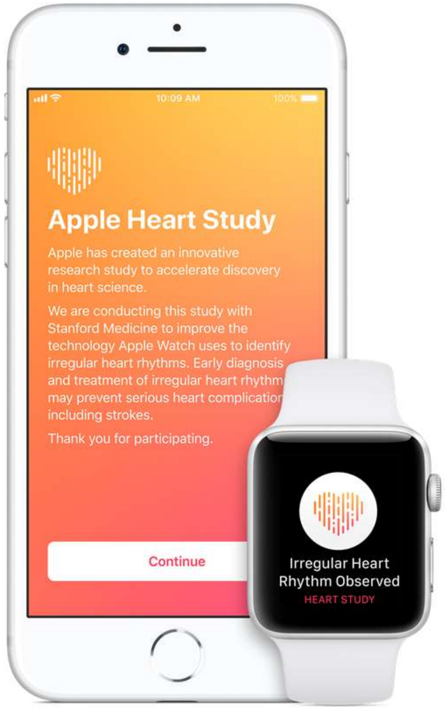
NCT # 03335800

Stanford MEDICINE

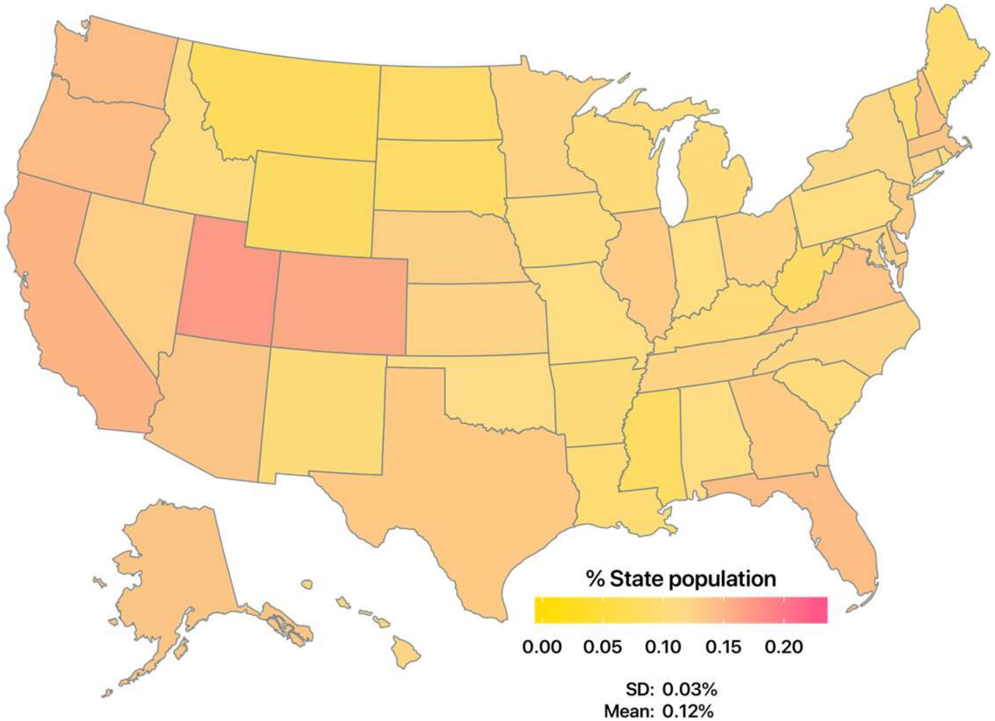
Overall Goal

To evaluate the ability of the irregular pulse notification algorithm to identify Afib and guide subsequent clinical evaluation

- ☐ Notification burden
- ☐ Subsequent Afib diagnosis
- ☐ Algorithm performance
- ☐ Safety
- ☐ Pragmatic and generalizable
- ☐ Scalable study procedures



Enrollment: 419,297; 24,626 age ≥ 65



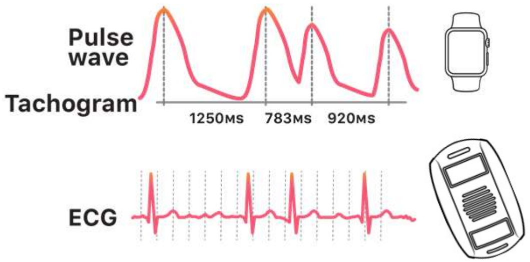
Enrollment by State Adjusted for Census Population

Enrollment:
Nov 29, 2017 – Jul 31, 2018

Last data collection:
Feb 25, 2019

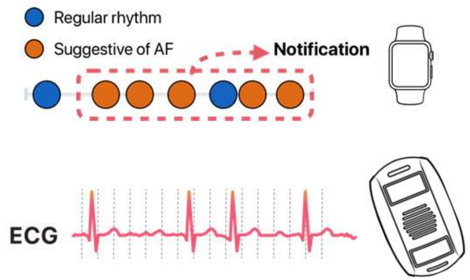
Accuracy: Positive Predictive Values

Irregular Tachograms



Afib on ECG Patch	Total Positive Tachograms	PPV* (97.5% CI)
1,489	2,089	0.71 (0.69–0.74)

Irregular Pulse Notifications



Afib on ECG Patch	Total Positive Notifications	PPV (95% CI)
72	**86**	0.84 (0.76–0.92)

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"Big data" to inform clinical questions

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PERSPECTIVE OPEN

It is time to learn from patients like mine

Saurabh Gombar[1,2], Alison Callahan[2], Robert Califf[3], Robert Harrington[2] and Nigam H. Shah[2]

Clinicians are often faced with situations where published treatment guidelines do not provide a clear recommendation. In such situations, evidence generated from similar patients' data captured in electronic health records (EHRs) can aid decision making. However, challenges in generating and making such evidence available have prevented its on-demand use to inform patient care. We propose that a specialty consultation service staffed by a team of medical and informatics experts can rapidly summarize 'what happened to patients like mine' using data from the EHR and other health data sources. By emulating a familiar physician workflow, and keeping experts in the loop, such a service can translate physician inquiries about situations with evidence gaps into actionable reports. The demand for and benefits gained from such a consult service will naturally vary by practice type and data robustness. However, we cannot afford to miss the opportunity to use the patient data captured every day via EHR systems to close the evidence gap between available clinical guidelines and realities of clinical practice. We have begun offering such a service to physicians at our academic medical center and believe that such a service should be core offering by clinical informatics professional throughout the country. Only if we launch such efforts broadly can we systematically study the utility of learning from the record of routine clinical practice.

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INTRODUCTION

Randomized controlled trials (RCTs) are the gold standard of clinical evidence and the bedrock of evidence-based medicine. However, the cost of conducting RCTs, their narrow inclusion criteria, and their focus on only a subset of patient demographics, conditions, and treatments limits their applicability in the majority of scenarios encountered daily by clinicians.[1] In 2011, Frankovich et al.[2] reported a case of using electronic health records (EHRs) to guide the clinical care of a patient in the absence of RCT-based evidence, and in 2014, Longhurst et al.[3] outlined a future in which health information systems help clinicians leverage patient data stored in the EHR at the point of care. Despite the promise of unlocking the treasure trove of EHR data to improve patient care, the state of affairs has not advanced much since 2011. The primary barriers are the methodological and operational challenges of distilling patient data into digestible clinical evidence that a physician can act on.

A common narrative in the popular press is that EHRs, combined with advanced computing and data science methods, are ready to transform healthcare. Given the prevalence of this perspective, and the increasing volume and availability of EHR data, one could imagine that it is feasible to extract knowledge with a high clinical value from EHRs in a fully automated manner with little expert input. However, much of the promise of the healthcare data revolution[4] is hype that fails to acknowledge the complex nature of clinical decision making.[5] A "one size fits all" solution is unlikely to work in such settings. Furthermore, medical practitioners have highlighted ethics and safety concerns[6,7] in turning over care decisions to machine-based systems that operate over incomplete and biased EHRs[8] without physician input. Shortliffe et al.[9] recently highlighted the six capabilities a system must possess in order to support clinical decisions including transparency, rapid turnaround, ease of use, the relevance of answer, respect for users, and solid scientific footing.

We believe that such challenges—of getting reliable data out of the EHR and satisfying the criteria of successful clinical decision support—are best overcome via a specialty consultation service. Such a service would use state-of-the-art analytic methods to glean reliable insights out of the EHR and have medical domain expertise to contextualize results for clinical decision making. Such a service would be staffed by a team comprised of a clinical informatics trained physician for interfacing with the requesting provider and to provide clinical context when interpreting findings, an EHR data specialist to create patient cohorts, and a data scientist to perform statistical analyses. The setup as a specialty consult is radically different from the popular paradigm of self-serve AI-enabled tools that undertake data processing behind the scenes and directly present the results to a physician for interpretation. We believe that an "expert in the loop" set up is necessary to strike a balance between efficiency and rigor given the limitations of the data, and the inference methods.[10]

We launched an IRB approved pilot of such a service at our academic medical center, to study the feasibility of integrating on-demand evidence into routine patient care. We propose that such a service should be core offering by clinical informatics professionals throughout the country. For many medical centers, a significant challenge in offering such a service—beyond the staffing—is the rapid creation of patient cohorts. Depending on available tools and personnel, cohort generation may take several weeks, which is untenable for care decisions that must be made within days. To enable the consult service, we have developed a search engine that indexes patient timelines for building cohorts

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These authors contributed equally: Saurabh Gombar, Alison Callahan

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The Stanford Informatics Consult Service

Given a specific case, provide a report with a descriptive summary of similar patients in Stanford's clinical data warehouse, the common treatment choices made, and the observed outcomes after specific treatment choices.

An institutional review board approved study (IRB # 39709)

http://greenbutton.stanford.edu

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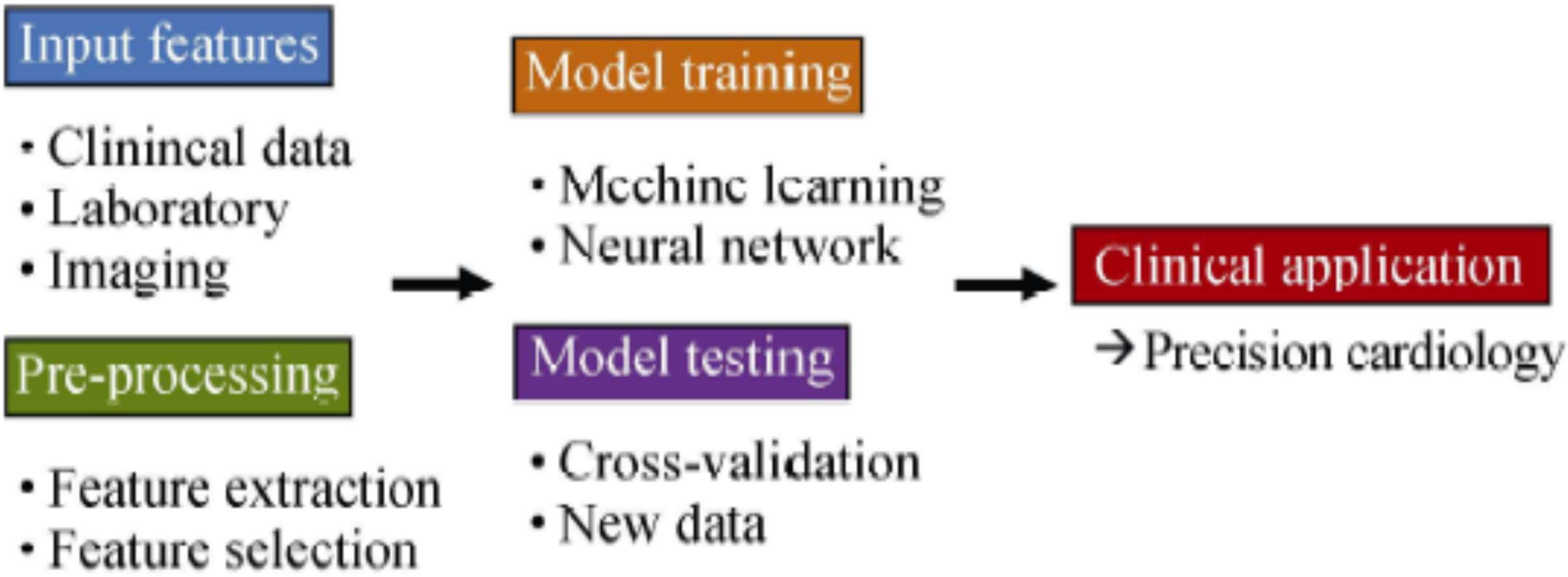
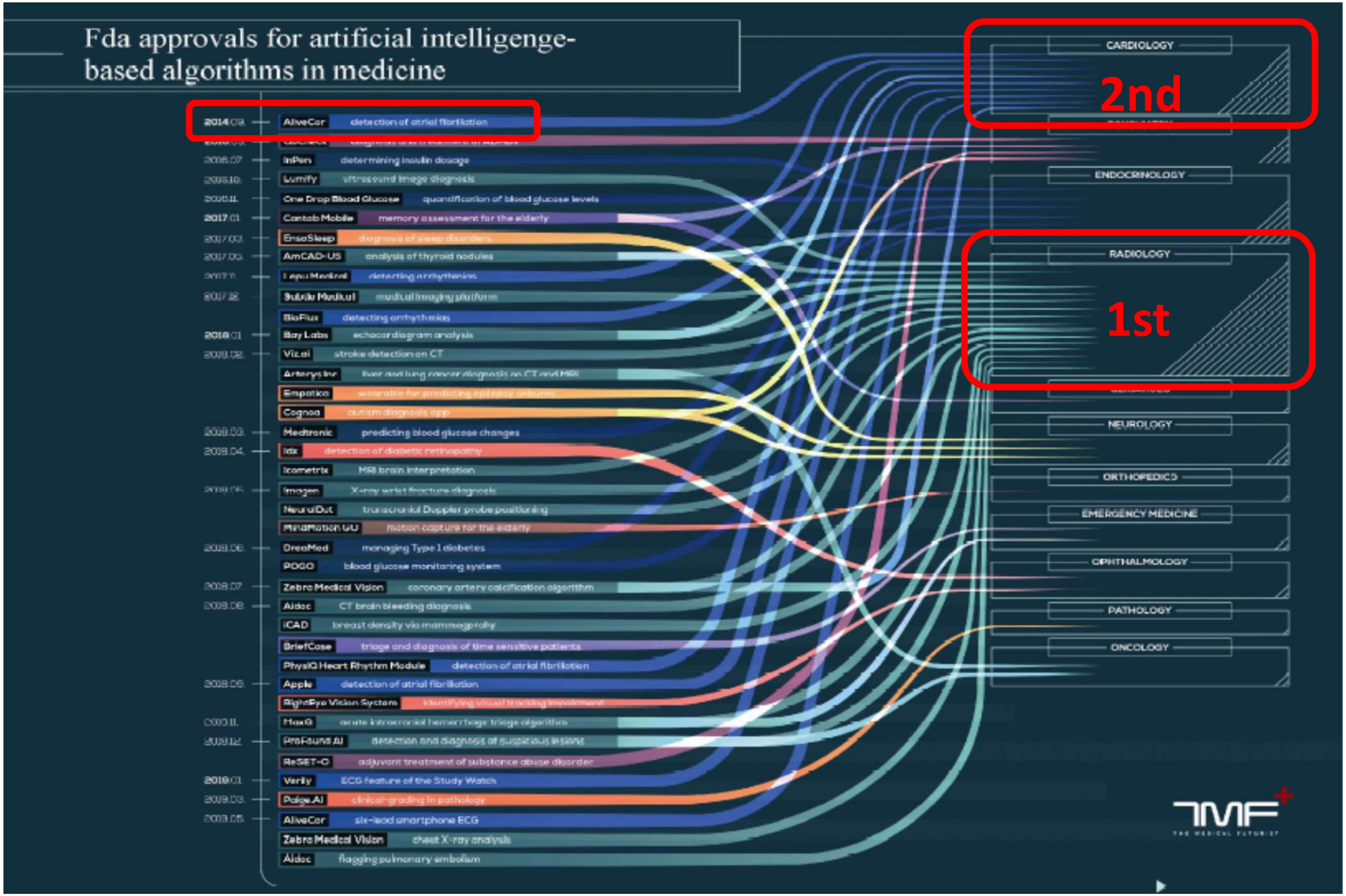
Machine learning approach



Cuocolo et al 2019


Fda approvals for artificial intelligenge-based algorithms in medicine
2014.09.
AliveCor
detection of atrial fibrillation
2016.07.
InPen
determining insulin dosage
Lumify
ultrasound image diagnosis
One Drop Blood Glucose
quantification of blood glucose levels
2017.01.
Cantab Mobile
memory assessment for the elderly
EnsoSleep
diagnosis of sleep disorders
AmCAD-US
analysis of thyroid nodules
detecting arrhythmias
BioFlux
detecting arrhythmias
2018.01.
Bay Labs
echocardiogram analysis
2018.02.
Viz.ai
stroke detection on CT
Empatica
Cognoa
2018.03.
Medtronic
predicting blood glucose changes
2018.04.
Idx
detection of diabetic retinopathy
Icometrix
MRI brain interpretation
Imagen
X-ray wrist fracture diagnosis
NeuralDut
transcranial Doppler probe positioning
2018.06.
DreaMed
managing Type 1 diabetes
POGO
blood glucose monitoring system
2018.07.
Zebra Medical Vision
coronary artery calcification algorithm
2018.08.
Aidoc
CT brain bleeding diagnosis
iCAD
breast density via mammography
BriefCase
triage and diagnosis of time sensitive patients
PhysIQ Heart Rhythm Module
detection of atrial fibrillation
2018.09.
Apple
detection of atrial fibrillation
ReSET-O
adjuvant treatment of substance abuse disorder
2019.01.
Verily
ECG feature of the Study Watch
2019.03.
Paige.AI
clinical grading in pathology
2019.05.
AliveCor
six-lead smartphone ECG
Zebra Medical Vision
chest X-ray analysis
Aidoc
flagging pulmonary embolism
CARDIOLOGY
2nd
ENDOCRINOLOGY
RADIOLOGY
1st
NEUROLOGY
ORTHOPEDICS
EMERGENCY MEDICINE
OPHTHALMOLOGY
PATHOLOGY
ONCOLOGY

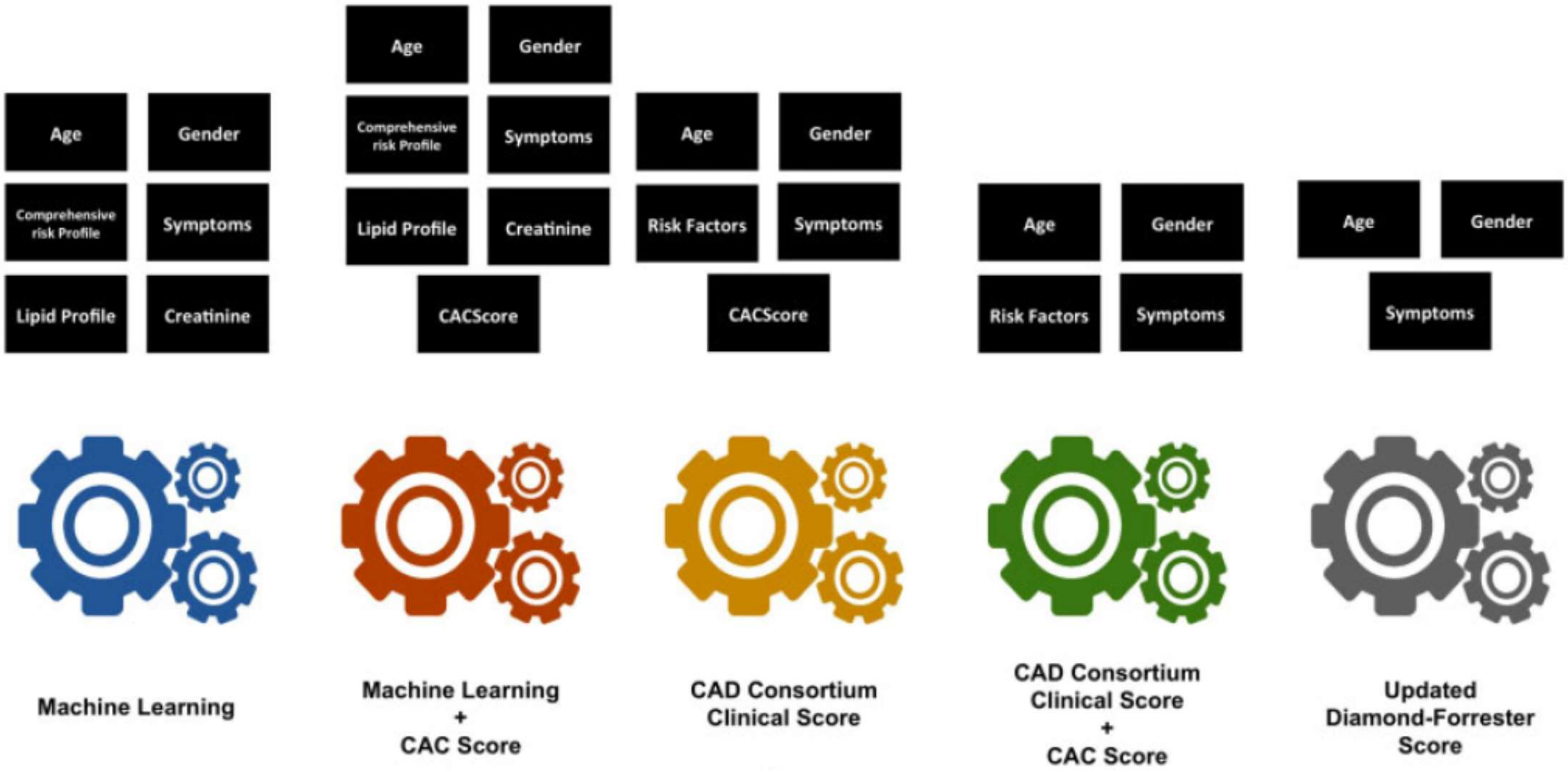
ESC
European Society
of Cardiology

European Heart Journal (2019) **0**, 1–9
doi:10.1093/eurheartj/ehz565

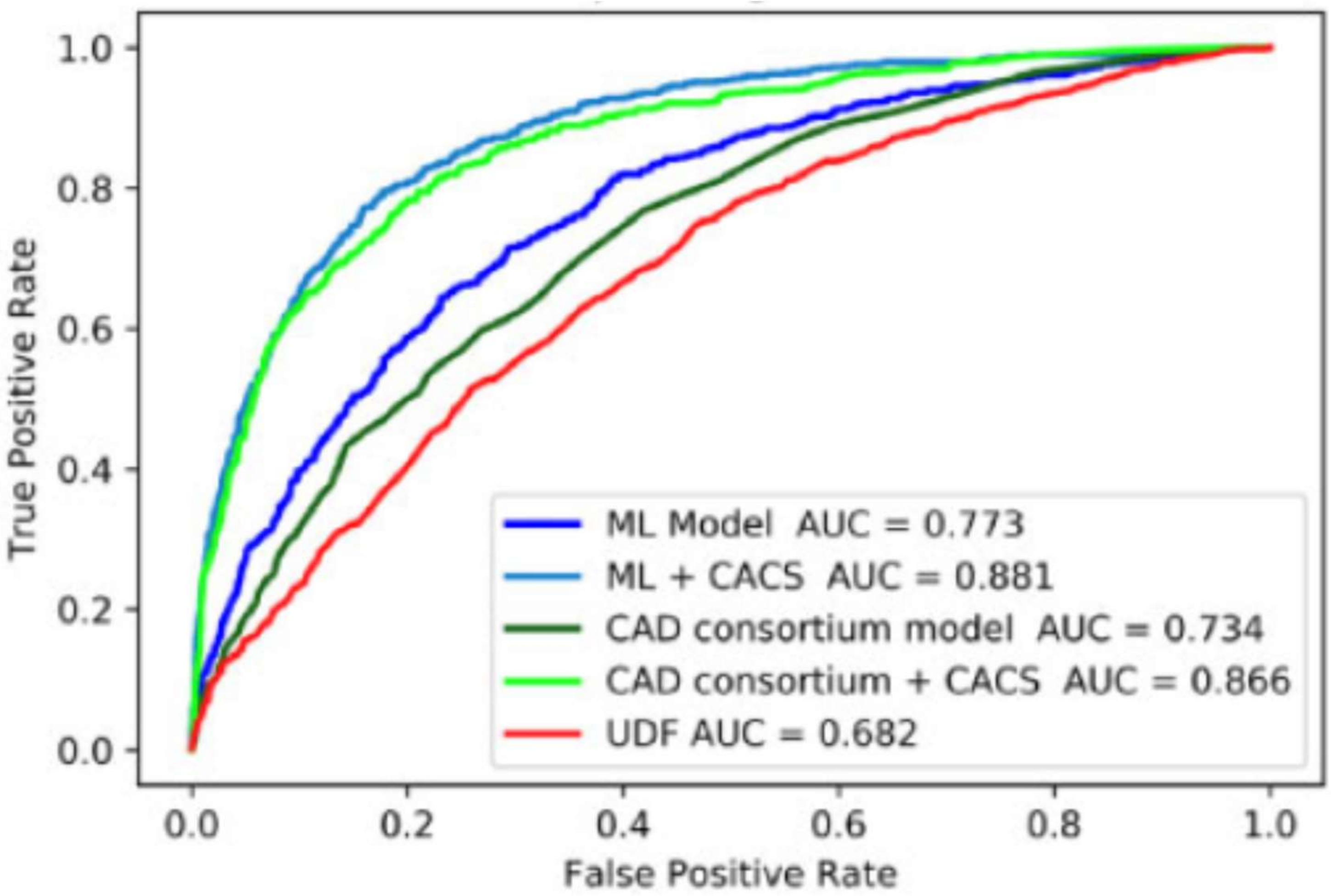
CLINICAL RESEARCH
Coronary artery disease

Machine learning of clinical variables and coronary artery calcium scoring for the prediction of obstructive coronary artery disease on coronary computed tomography angiography: analysis from the CONFIRM registry

Predictive models for obstructive CAD in > 13,000 subjects



ROC Curves for the various models



JACC: CARDIOVASCULAR IMAGING VOL. ■, NO. ■, 2019

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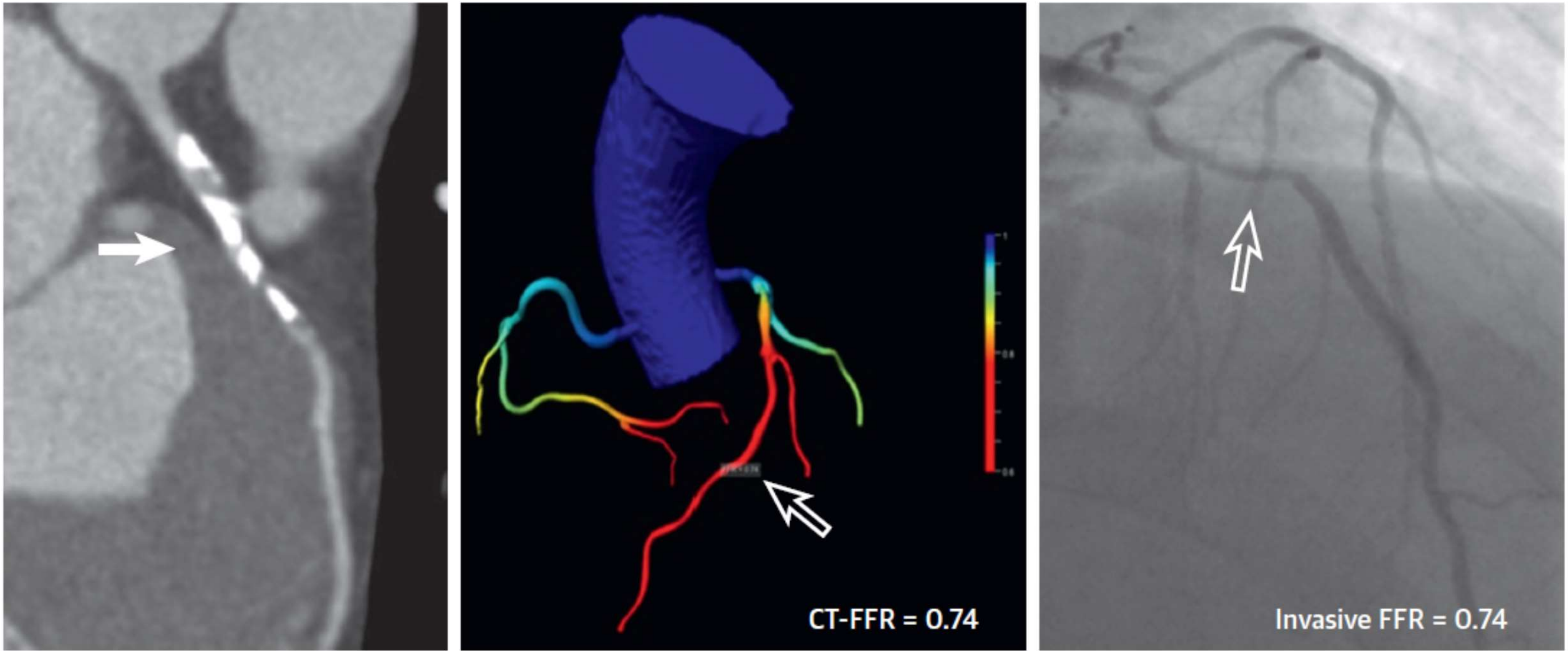
ORIGINAL RESEARCH

Influence of Coronary Calcium on Diagnostic Performance of Machine Learning CT-FFR

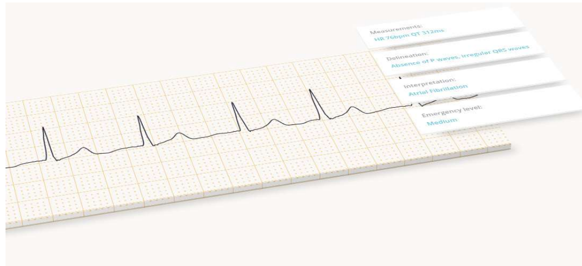
Results From MACHINE Registry

Christian Tesche, MD,[a,b,c] Katharina Otani, PhD,[d] Carlo N. De Cecco, MD, PhD,[a] Adriaan Coenen, MD,[e,f] Jakob De Geer, MD, PhD,[g] Mariusz Kruk, MD, PhD,[h] Young-Hak Kim, MD, PhD,[i] Moritz H. Albrecht, MD,[a,j] Stefan Baumann, MD,[a,k] Matthias Renker, MD,[a,l] Richard R. Bayer, MD,[a,m] Taylor M. Duguay, BS,[a] Sheldon E. Litwin, MD,[a,m] Akos Varga-Szemes, MD, PhD,[a] Daniel H. Steinberg, MD,[m] Dong Hyun Yang, MD, PhD,[n] Cezary Kepka, MD, PhD,[h] Anders Persson, MD, PhD,[g] Koen Nieman, MD,[e,f,o] U. Joseph Schoepf, MD[a,m]

Machine Learning CT-FFR vs invasive FFR



Current Artificial Intelligence applications in clinical care



- **Diagnostics**
  - Atrial fibrillation detection using ECG data (Cardiologs®)
  - Diastolic dysfunction detection using 2D US images
- **Cardiac Imaging**
  - Virtual model of the heart to predict failure from echocardiography images (Philips HeartModel^{AI})
  - Coronary calcium scoring from non-contrast CT scans (Zebra Medical Vision)
- **Therapy selection**
  - Selection of care pathways based on risk, costs predicted by artificial intelligence (KenSci, Healthcheck, Corti Labs)
- **Continuous monitoring**

  - Continuos heart rate, ECG, biometric and user’s behavior tracking to predict early signs of cardiovascular anomalies (Kardia, Fitbit, Cardiogram,…)

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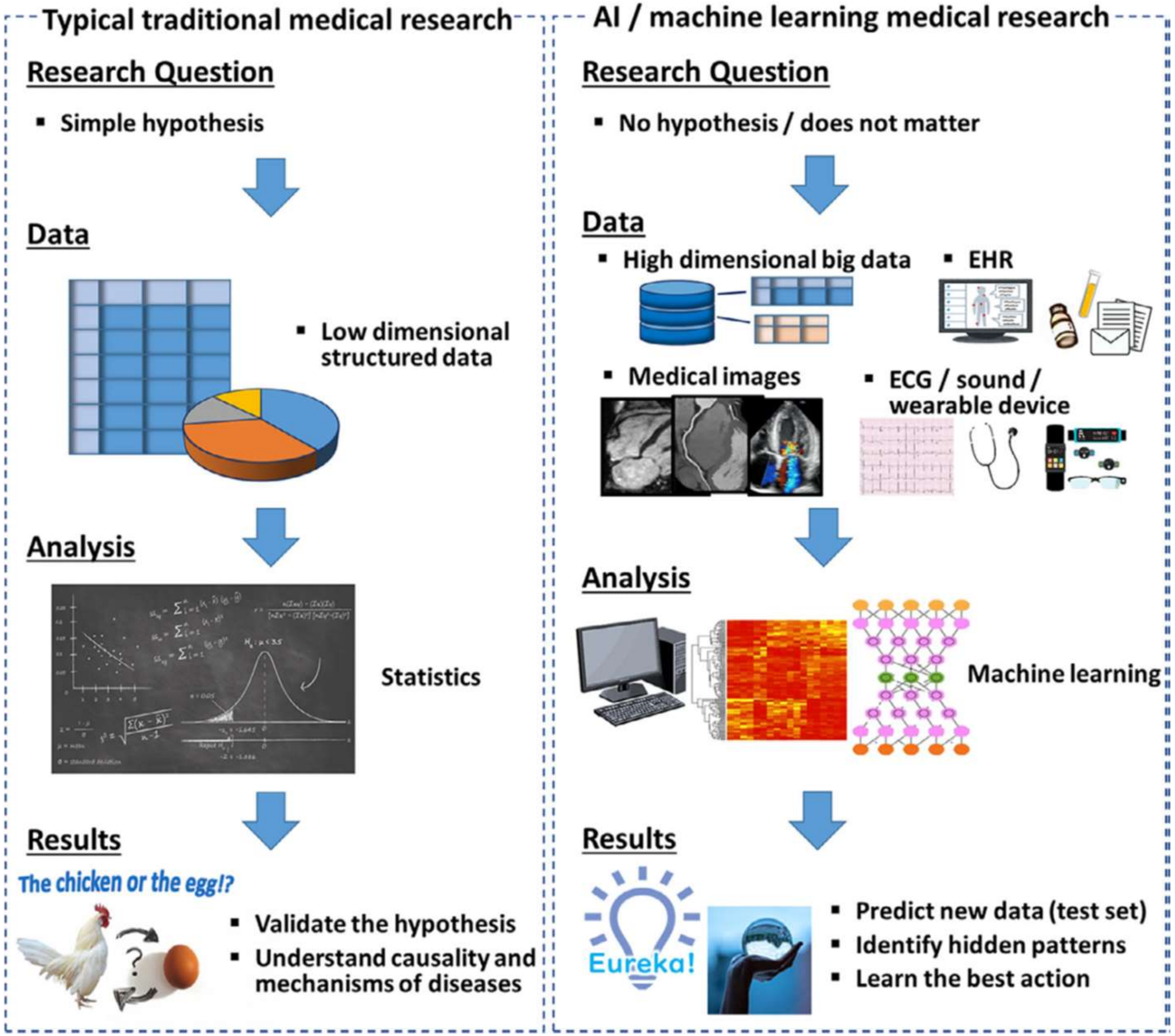
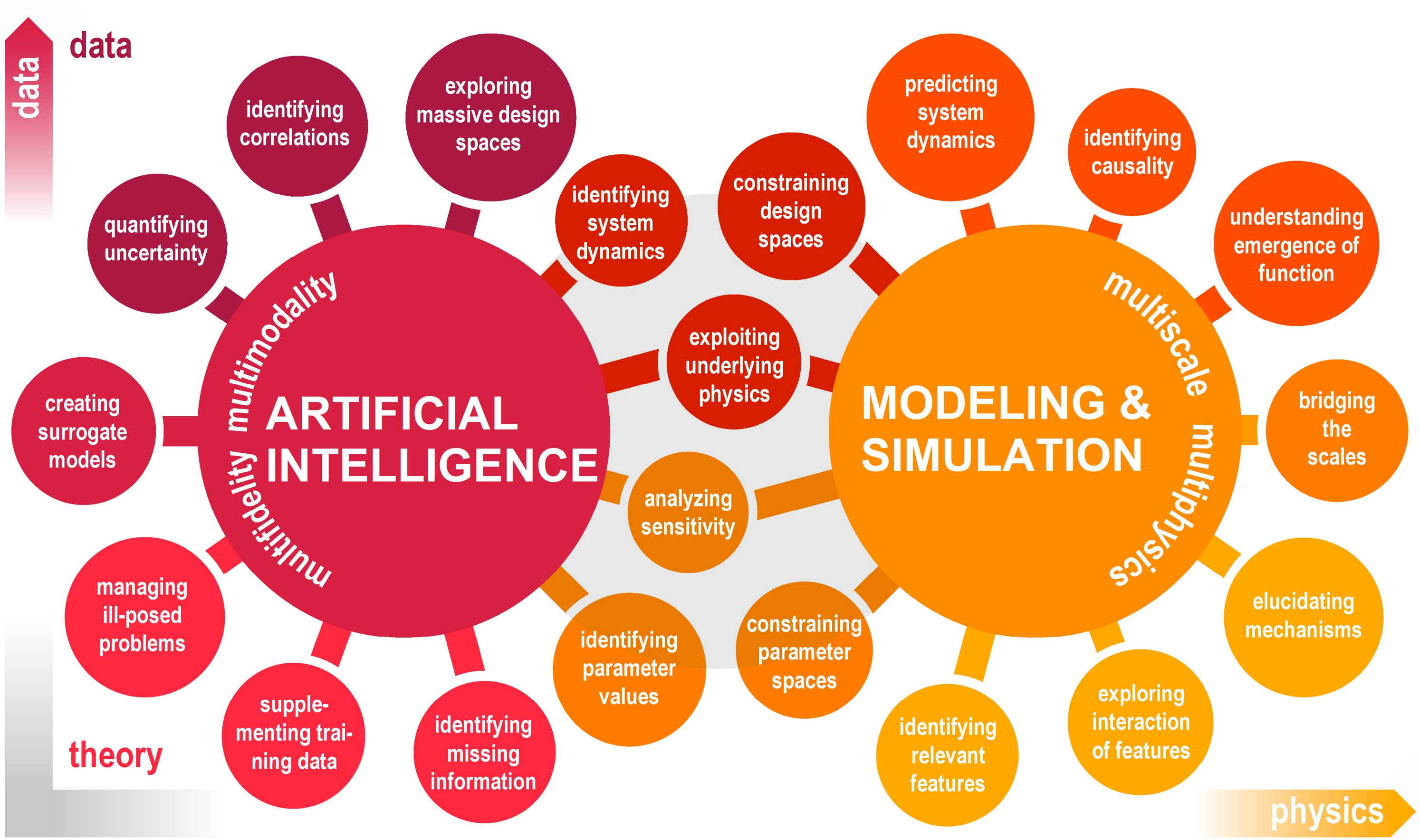
Technological innovations impacting the quality of care

Artificial Intelligence: Hypothesis-free and data-driven



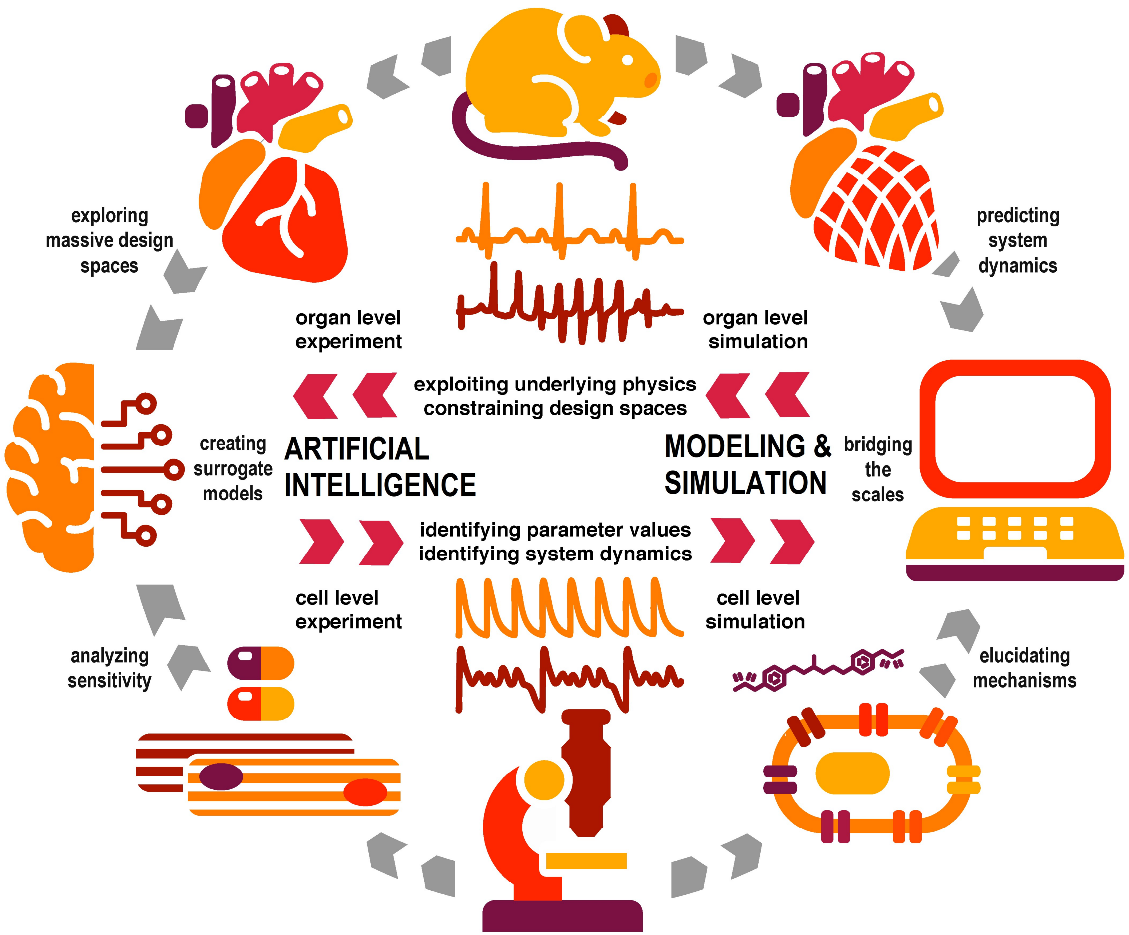
[Kagiyama et al., 2019]

On one side **artificial intelligence reveals *correlation***.
On the other side, **modeling & simulation reveals *causality***.



[adapted from Alber et al., 2019]

Technological impact in the near future: **integration of artificial intelligence and modeling** to better understand the cardiac system, for which the underlying data are incomplete and the physics are not yet fully understood

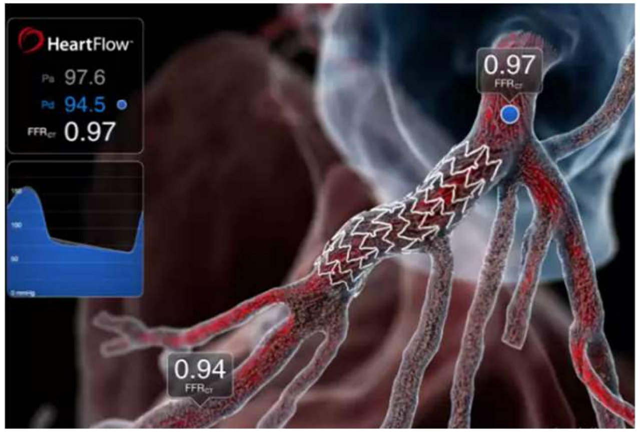


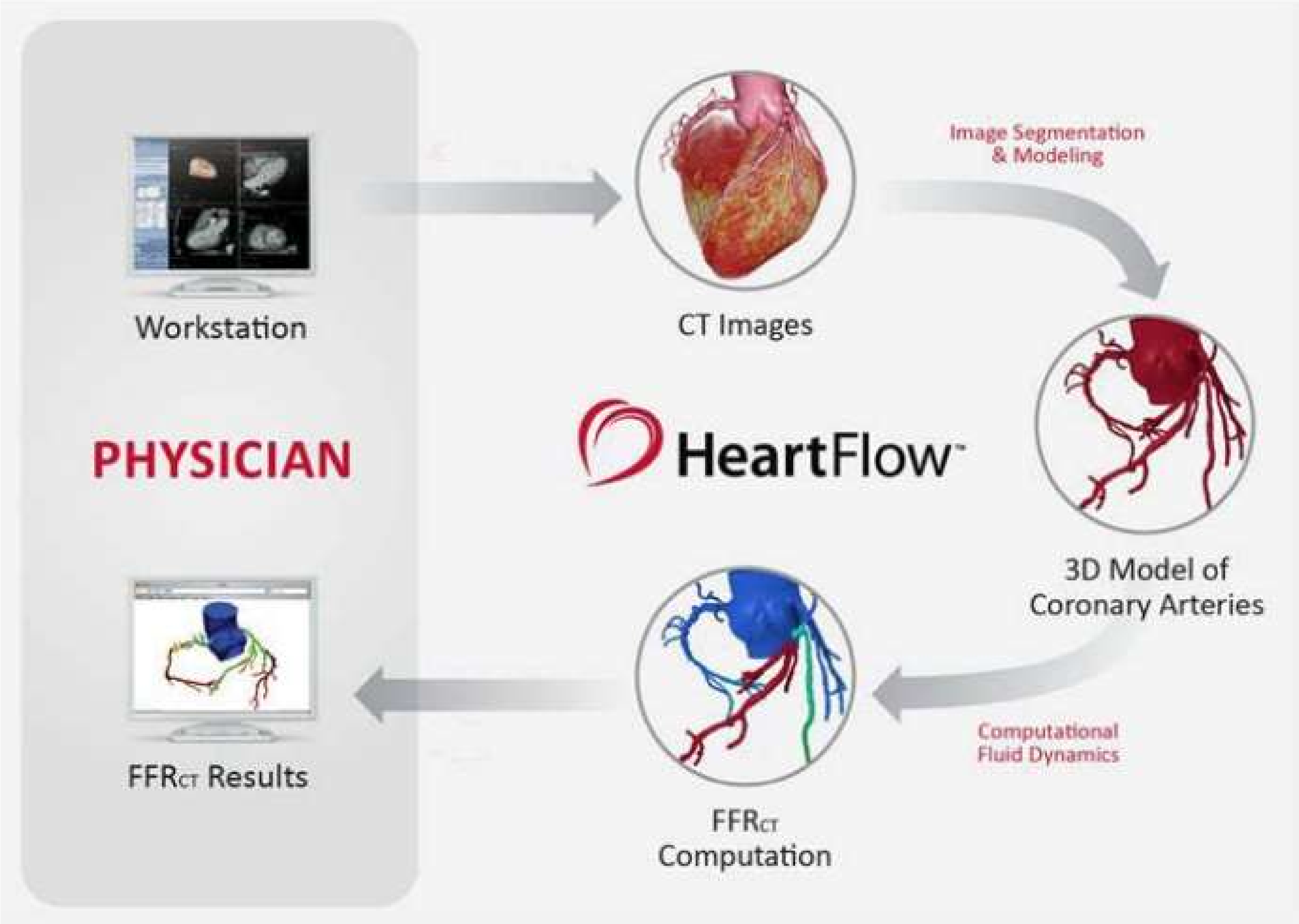
[adapted from Alber et al., 2019]

Current Modeling & Simulation applications in clinical care

Modeling & Simulation as a medical device

- HeartFlow®
- CardioInsight®





[www.heartflow.com]

Yes, new technology will profoundly impact the quality of care

It will be our duty to master it and combine it with the understanding of our patients and their need

THANK YOU
for your
ATTENTION!

Many more Artificial Intelligence applications to come…

Data Structure	Year	First Author	Journal/Conference	Task	Summary
Structured data					
	2016	Motowani	Eur Heart J	Classification: Prognostic prediction	Using 69 clinical and CT parameters of 10 030 CAD patients, a ML model predicted mortality better than traditional statistics
	2018	Kakadiaris	JAHA	Classification: Prognostic prediction	Using 9 parameters that consist of ACC/AHA risk calculator, a ML model showed better prediction than original ACC/AHA risk score.
	2016	Narula	JACC	Classification: Diagnosis of HCM	Using clinical and echocardiographic parameters, ML algorithms discriminated HCM from ATH with 87% sensitivity and 82% specificity.
	2019	Lancaster	JACC CV Imaging	Clustering	Using echocardiographic parameters that guidelines recommend for assessment of LVDD, hierarchical clustering identified clusters that discriminate patient prognosis better than guidelines-based classification
	2019	Casaclang-Verzosa	JACC CV Imaging	Clustering with dimensionality reduction	Topological data analysis was able to visualize patient-patient similarity network that is created from 4 parameters. Relative location of patients in the network were associated with disease phenotypes and prognosis.
Unstructured data					
Echocardiographic images	2018	Zhang	Circulation	Classification: Automatic interpretation of echocardiography	Using 14 035 echocardiograms, CNN enabled automatic classification of views, identification of chambers, measurements of cardiac volumes, and discrimination of diseases from healthy controls (see text for details)
MRI images	2019	Zhang	Radiology	Classification: Prediction of MI from non-enhanced MRI	In 212 patients and 87 controls, algorithms were able to detect chronic MI (validated by LGE) with 90% sensitivity and 99% specificity using nonenhanced cine MRI.
CT images	2016	Shandmi	Med Image Anal	Classification: Coronary artery calcium in a voxel	Using 3D CTA of 250 patients, after localization of volume of interest using 3 CNNs, 2 CNNs were used to classify voxels to calcium or noncalcium. Agatston score calculated based on the voxel classification showed excellent agreement with reference standard (accuracy 83%).
ECG signals	2019	Hannun	Nat Med	Classification: Arrhythmia detection	Using 91 232 single-lead ECG, trained algorithm showed better prediction of 12 types of heart rhythm than cardiologist (F-measure 0.84 vs 0.78).
Heart sound signals	2016	Potes	2016 CinC	Classification: Normal and abnormal heart sound	Combination of AdaBoost and CNN showed 94.2% sensitivity and 77.8% specificity for identifying abnormal heart sound in PhysioNet/CinC data set.
EHR	2019	Mallya	arXiv	Classification: Prognostic prediction	Using >23 000 patients time-series data, LSTM algorithm successfully predicted the onset of heart failure 15 mo in advance (AUC 0.91)
EHR: medical letters (text)	2019	Diller	Eur Heart J	Classification: Diagnosis, symptoms and prognosis	Using natural language processing, diagnosis (accuracy 91%) and symptoms (90.6%) were extracted from medical letters. Also, prognostic prediction using the same data was useful (HR 34.0)

ANN, artificial neural network; ATH, athlete; CAD, coronary artery disease; CNN, convolutional neural network; DNN, deep neural network; HCM, hypertrophic cardiomyopathy; HR, hazard ratio; LGE, late gadolinium enhancement; LSTM, long short time memory; LVDD, left ventricular diastolic dysfunction; ML, machine learning; RF, random forest; SVM, support vector machine.

[Kagiyama et al., 2019]