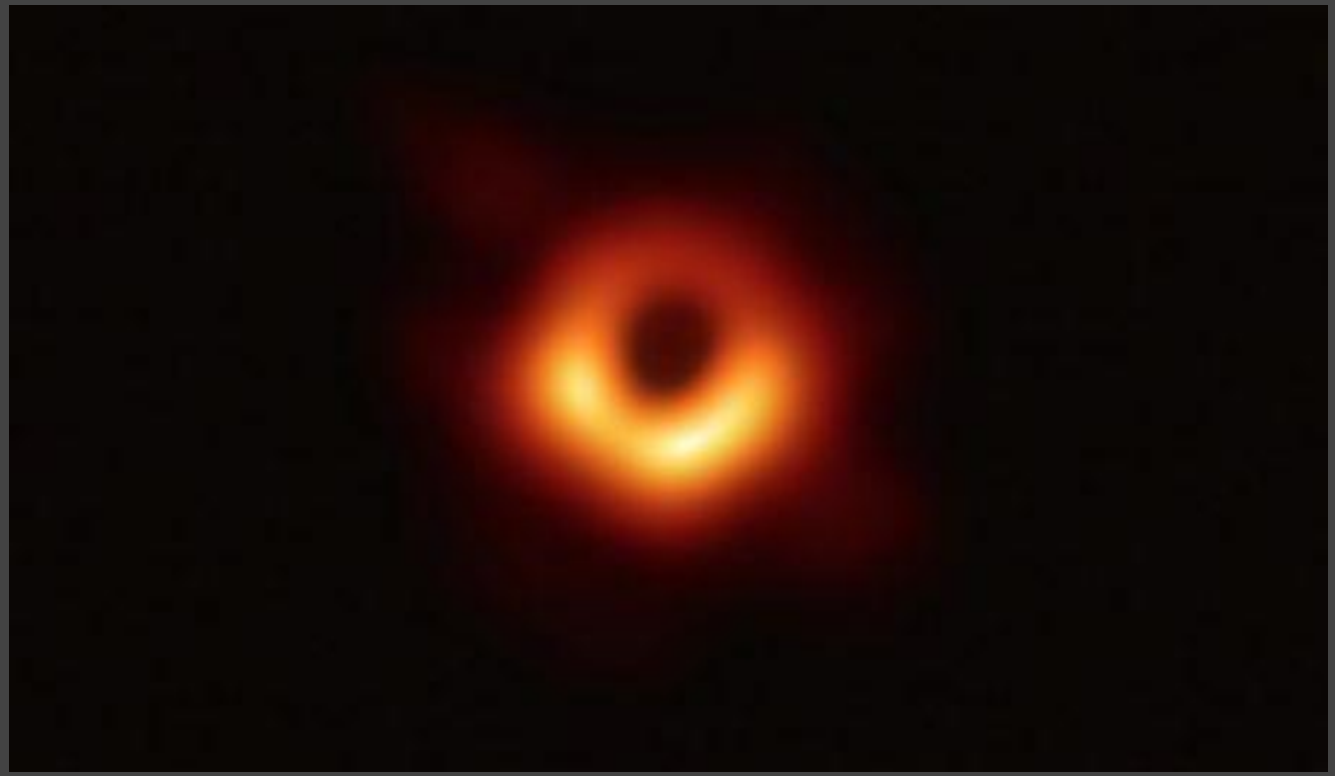
UCLouvain
Institut de recherche expérimentale et clinique

Cliniques universitaires SAINT-LUC UCL BRUXELLES

Digital tools in laboratory medicine

Prof. Damien Gruson



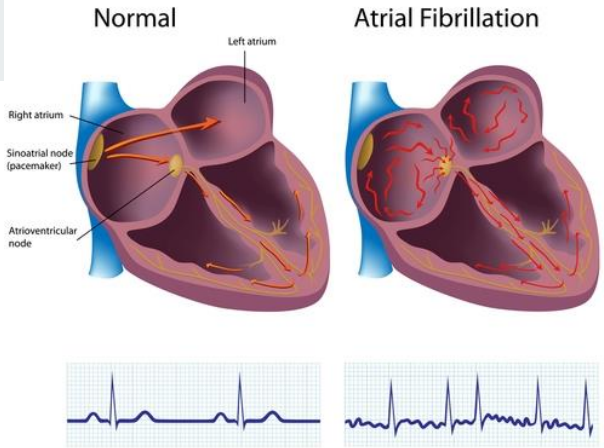
- **Digital Health is now the third largest industry in the European health sector, after pharmaceuticals and medical devices.**

- **The digital market in healthcare is spectacular:**
  - **More that 325000 health applications**
  - **More than 5 billion dollars investment into digital health startups**
  - **More than 340000 wearable devices available**

The Burden...

Atrial Fibrillation

"A new millenium epidemic"



11

Million people affected in Europe

2%

of people younger than 65 yrs

9%

of people 65 yrs and older

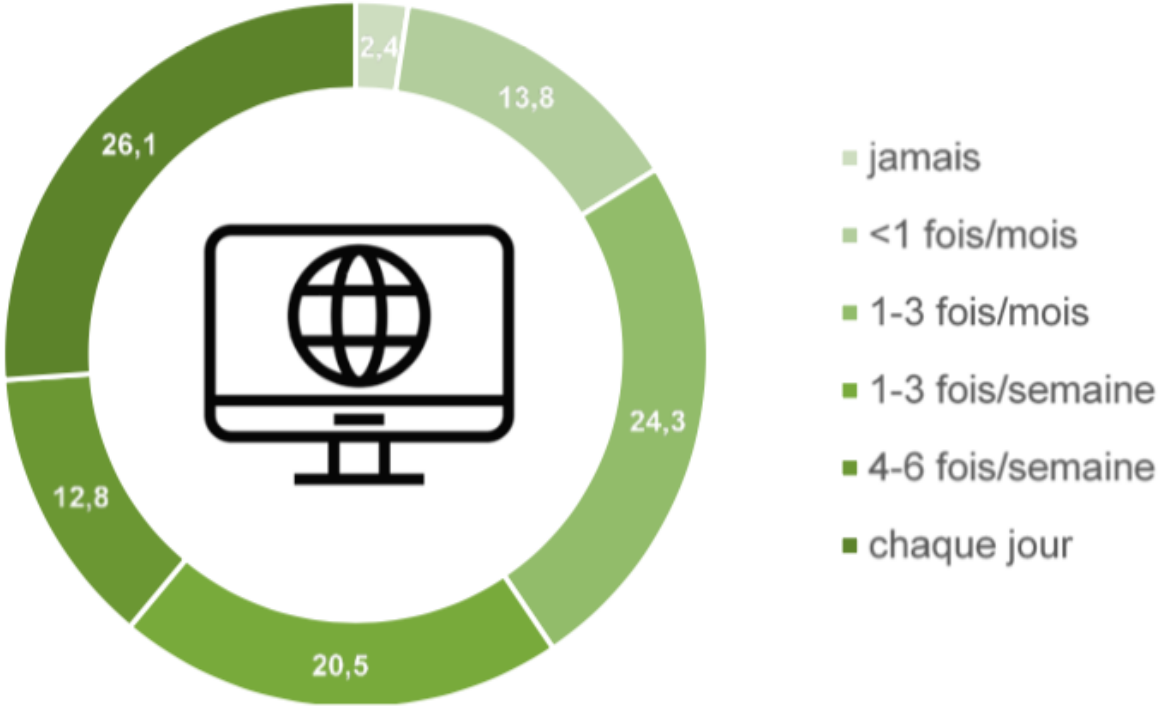
Sources: european society of cardiology, https://www.healthline.com, GARFIELD-AF

The shift: from Care to Cure

- ***"Healthcare systems need to move beyond reform and transform services delivered outside hospitals for the chronically ill patients"*** *John Brosky*

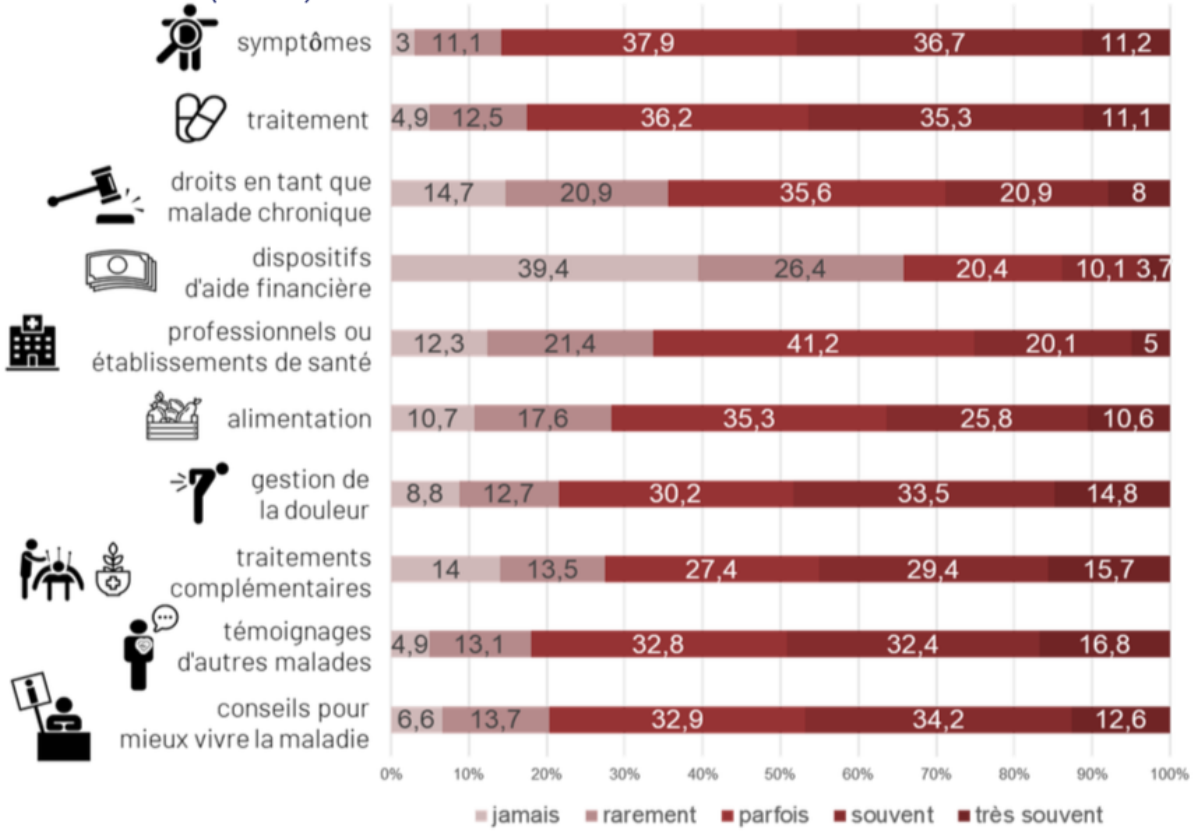
- ***Patient centric***

A quelle fréquence utilisez-vous internet pour vous aider dans la recherche d'information, le suivi et la gestion de votre maladie chronique ? (N = 954)



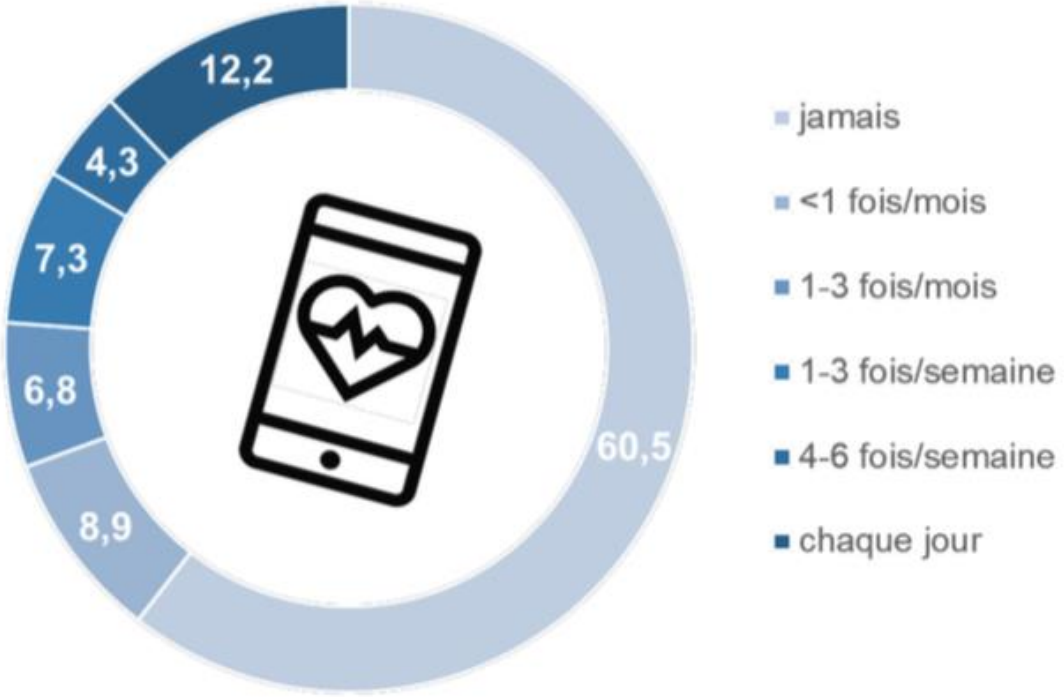
Source: étude Institut Mines-Télécom Business school

De manière plus précise, à quelle fréquence consultez-vous les informations suivantes ? (N=954)



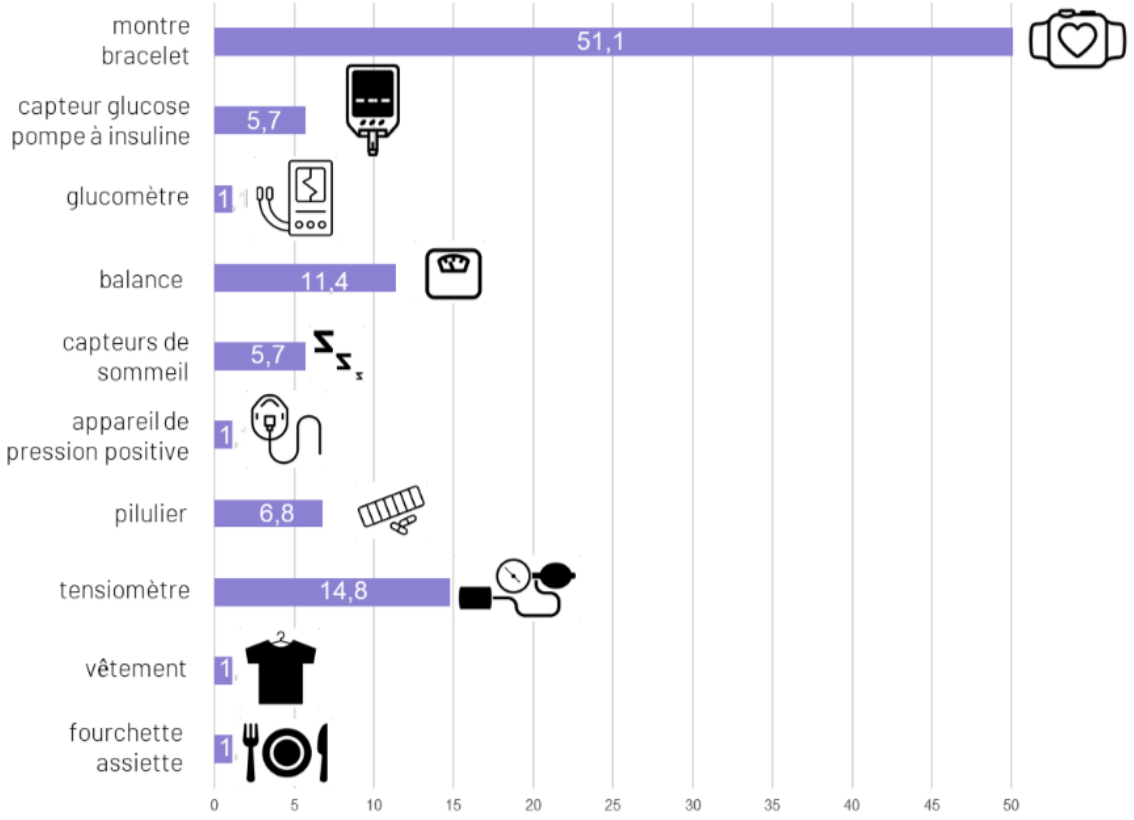
Source: étude Institut Mines-Télécom Business school

A quelle fréquence utilisez-vous les applications mobiles pour vous aider dans la recherche d'information, le suivi et la gestion de votre maladie chronique ? (N = 954)



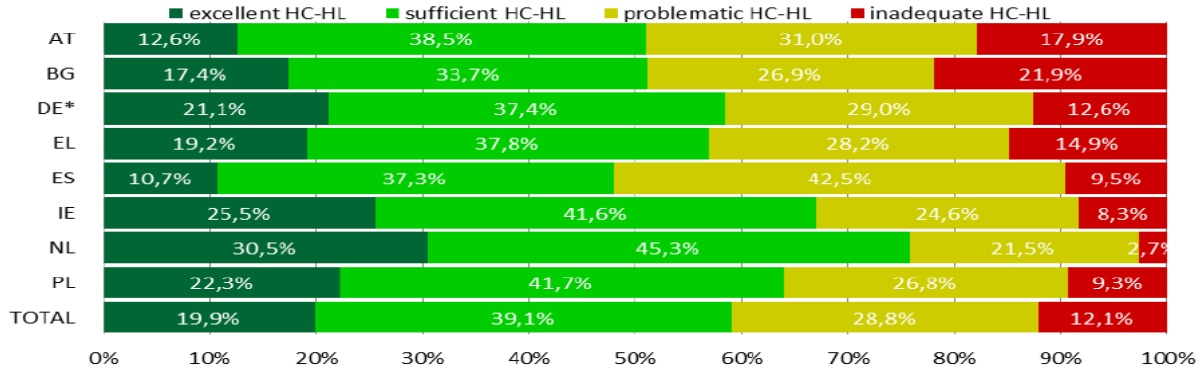
Source: étude Institut Mines-Télécom Business school

Quel type d'objet connecté utilisez-vous ? (N=88)

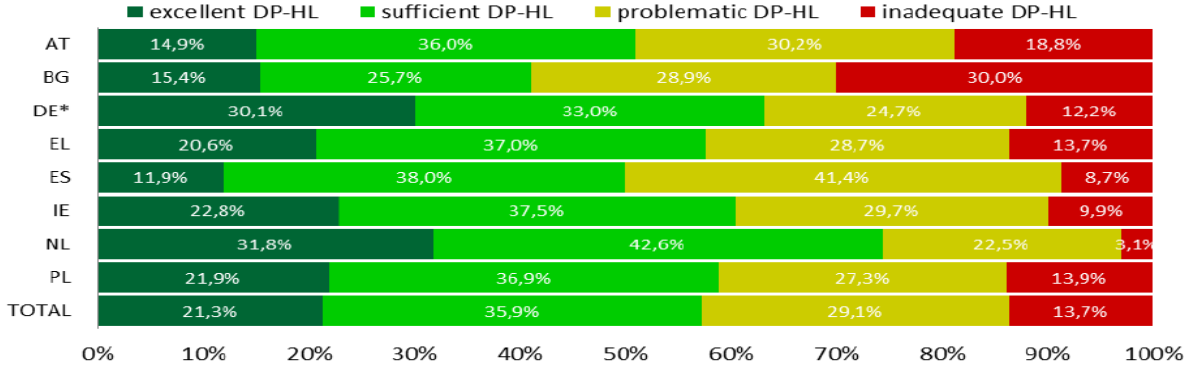


Source: étude Institut Mines-Télécom Business school

Graph 11: Percentages of Health Care Health Literacy Levels Thresholds for Countries and Total



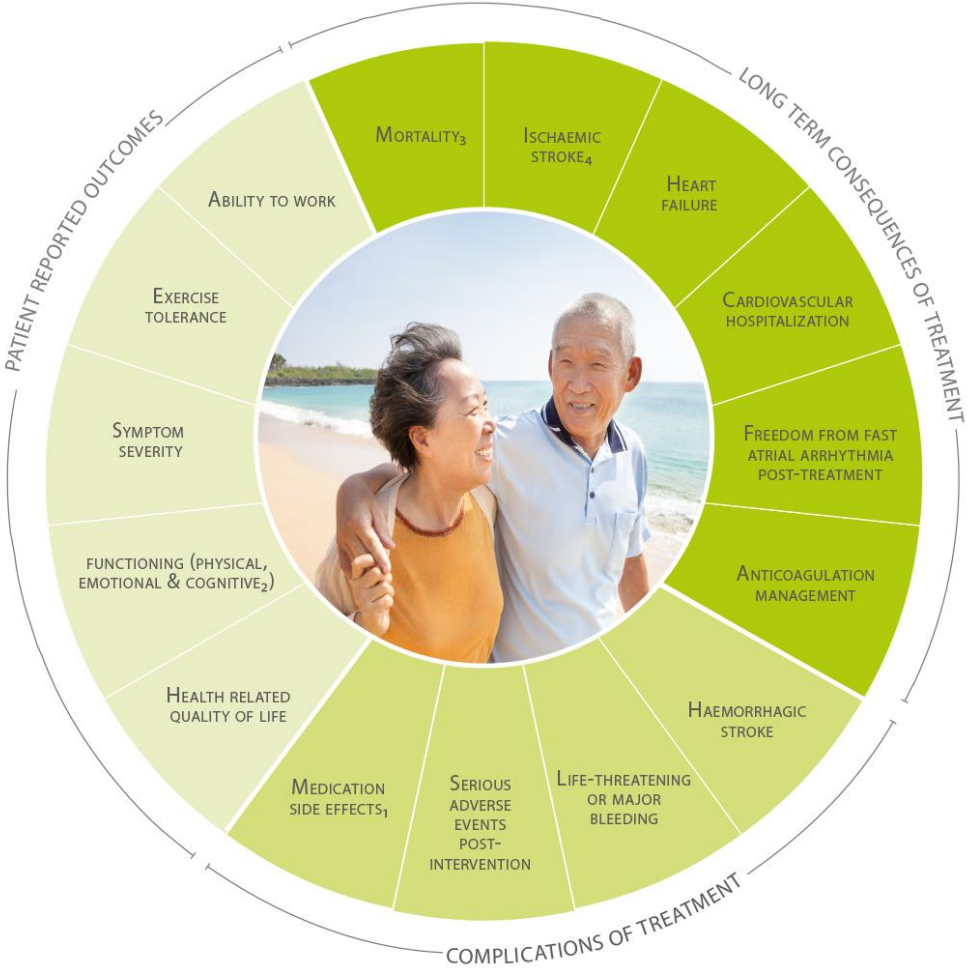
Graph 12: Percentages of Disease Prevention Health Literacy Levels Thresholds for Countries and Total



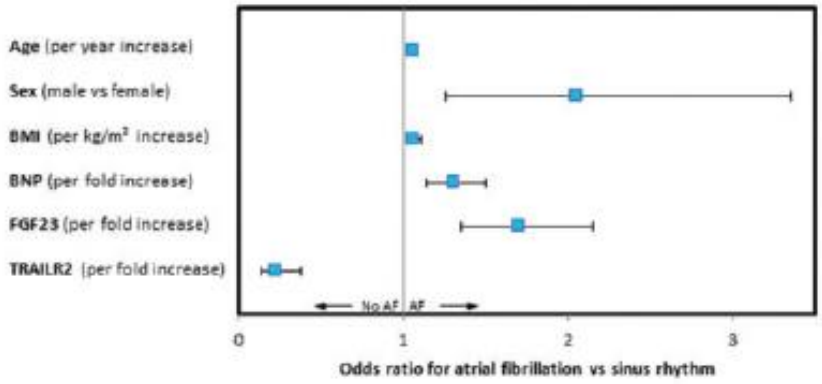
HLS-EU CONSORTIUM (2012): COMPARATIVE REPORT OF HEALTH LITERACY IN EIGHT EU MEMBER STATES. THE EUROPEAN HEALTH LITERACY SURVEY HLS-EU , ONLINE PUBLICATION: HTTP://WWW.HEALTH-LITERACY.EU

Atrial Fibrillation

ICHOM



www.ichom.org



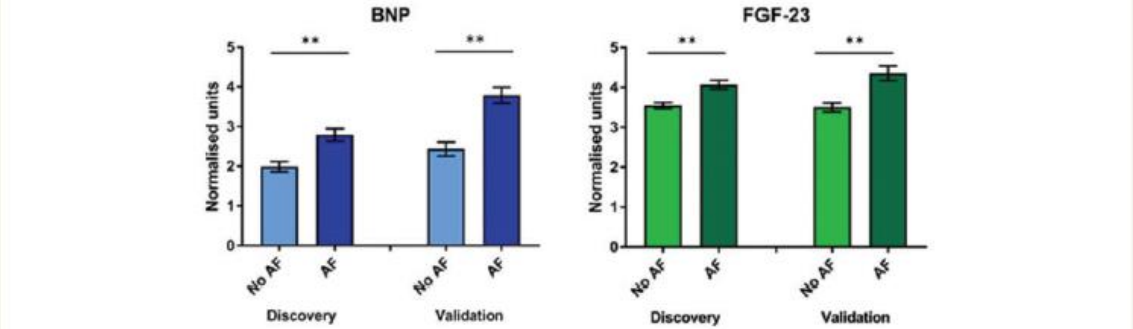


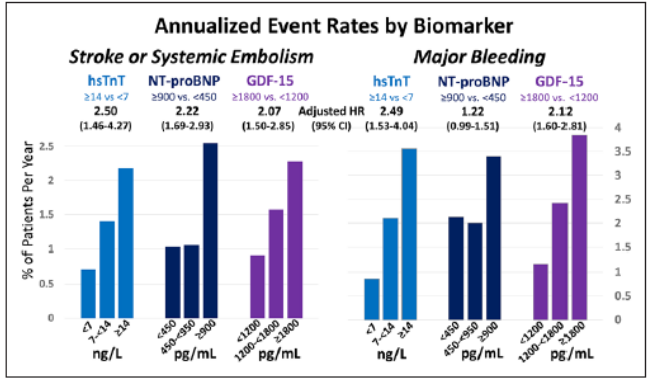
Figure 4 Comparison of biomarker levels between patients with and without atrial fibrillation. Elevated brain natriuretic peptide and fibroblast growth factor 23 levels observed in atrial fibrillation groups in both discovery and validation cohorts. **P< 0.001; error bars represent the SEM. BNP, brain natriuretic peptide; FGF-23, fibroblast growth factor 23.

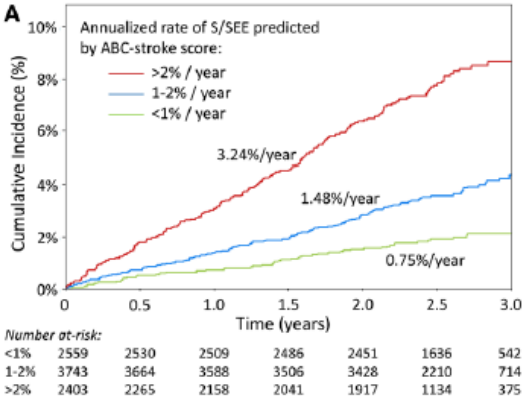
Three simple clinical risk factors (age, sex, and BMI) and two biomarkers (elevated BNP and elevated FGF-23) identify patients with AF.

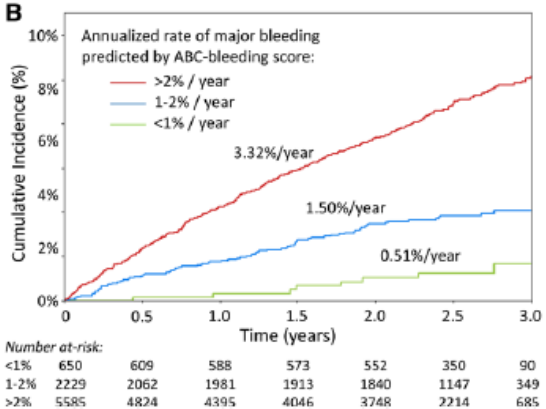
Chua et al.; 2019

The components of the ABC-stroke score include age, NT-proBNP, high-sensitivity cardiac troponin T (hsTnT), and prior stroke/transient ischemic attack (TIA),

the components of the ABC-bleeding score include age, growth differentiation factor-15 (GDF-15), hsTnT, hemoglobin, and history of bleeding







Morrow et al.; 2019

Trends: Point of Care

Daily home BNP monitoring in heart failure for prediction of impending clinical deterioration: results from the HOME HF study

Table 4 Poisson regression models for the primary event rate (events = 27, exposure = 17 362 patient days) with time-varying predictors

Variable	β	SE	*P*-value	Hazard ratio (95% CI)
Univariate models				
Log fBNP(t)	0.797	0.208	0.0001	2.22 (1.48–3.34)
Log fBNP(day1)	0.375	0.214	0.0793	1.46 (0.96–2.21)
Log Ratio(t)	0.996	0.293	0.0007	2.71 (1.52–4.81)
Weight gain	1.171	0.612	0.0559	3.22 (0.97–10.71)
Multivariate model where fBNP(t) is adjusted for weight gain				
Log fBNP(t)	0.767	0.208	0.0002	2.15 (1.43–3.24)
Weight gain	0.886	0.618	0.1520	2.42 (0.72–8.14)
Multivariate model where fBNP(t) is adjusted for initial fBNP				
Log fBNP(t)	1.186	0.294	0.0001	3.27 (1.84–5.83)
Log fBNP(day1)	-0.565	0.321	0.0783	0.57 (0.30–1.07)
Multivariate model where Ratio(t) is adjusted for initial fBNP				
Log Ratio(t)	1.186	0.294	0.0001	3.27 (1.84–5.83)
Log fBNP(day1)	0.621	0.231	0.0072	1.86 (1.18–2.93)

BNP, B-type natriuretic peptide; CI, confidence interval; SE, standard error.
The time-varying predictors are the natural log of fBNP and weight gain on each day of the monitoring period. Weight gain of ≥5 lb over 5 days was treated as a dichotomous predictor. The value of fBNP on the first day of the monitoring period is denoted fBNP(day1). The Ratio(t) is defined as fBNP(t)/fBNP(day1). The log is the natural log. The intercepts of the models are not shown.

McDonald et al.; 2018

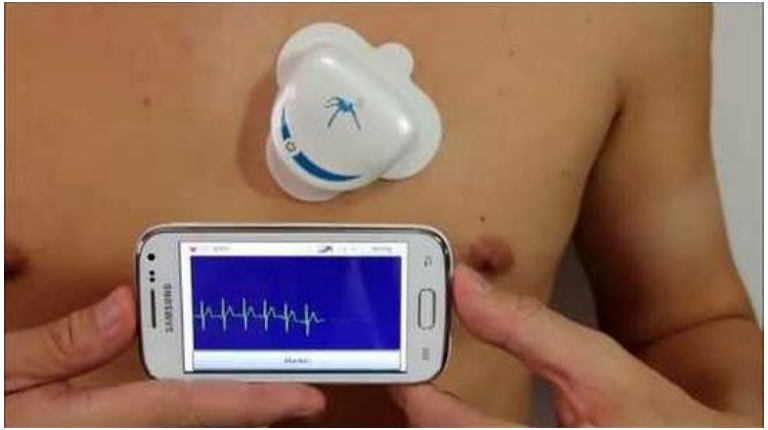
Trends: Point of Care

Table 1. Factors associated with good analytical quality in a logistic regression analysis.

Variable	CRP, OR (95% CI)	Glucose, OR (95% CI)	Hemoglobin, OR (95% CI)
Number of participations in the EQAS			
Once	1	1	1
2-10 times	1.16 (1.05-1.28)	1.50 (1.37-1.64)	1.01 (0.88-1.16)
11-19 times	1.37 (1.22-1.54)	1.76 (1.58-1.96)	1.22 (1.04-1.43)
Type of participant			
GP office	1	1	1
Nursing home	0.85 (0.76-0.95)	1.14 (1.02-1.27)	0.60 (0.52-0.69)
Emergency primary healthcare	0.73 (0.63-0.82)	0.91 (0.76-1.09)	0.61 (0.49-0.77)
Occupational healthcare	0.68 (0.60-0.88)	0.91 (0.76-1.10)	0.70 (0.56-0.87)
Others	0.84 (0.63-1.13)	1.06 (0.80-1.40)	0.51 (0.38-0.66)
Type of person performing the analysis			
Medical laboratory scientist	1	1	1
Medical secretary	0.85 (0.74-0.96)	0.89 (0.79-1.00)	0.63 (0.51-0.77)
Nurse	0.82 (0.70-0.95)	0.81 (0.71-0.93)	0.50 (0.40-0.63)
Clinician	0.66 (0.54-0.82)	0.67 (0.55-0.82)	0.38 (0.28-0.51)
Number of analyses per week			
1-9	1	1	1
10-25	1.11 (1.01-1.22)	1.1 (1.03-1.18)	1.18 (1.07-1.31)
≥26	1.30 (1.17-1.45)	1.21 (1.11-1.31)	1.34 (1.16-1.54)
Frequency of internal QC			
Weekly	1	1	1
Monthly	0.84 (0.77-0.93)	0.92 (0.83-1.03)	0.78 (0.69-0.89)
When opening a new reagent or detecting errors	0.86 (0.80-0.92)	0.88 (0.82-0.94)	0.82 (0.74-0.90)
Never	0.83 (0.72-0.97)	0.83 (0.74-0.92)	0.73 (0.62-0.87)
Instrument changed			
No	1	1	1
Yes	1.07 (0.93-1.23)	0.89 (0.80-0.99)	0.96 (0.79-1.16)
Expiration date on reagents			
>60 days to expiration date	1	1	1
≤60 days to expiration date	0.74 (0.49-1.12)	0.65 (0.57-0.75)	0.69 (0.55-0.86)
Expired reagent	0.84 (0.70-1.01)	0.94 (0.84-1.05)	0.85 (0.70-1.03)

Bukve et al.; 2016

Trends: IoT



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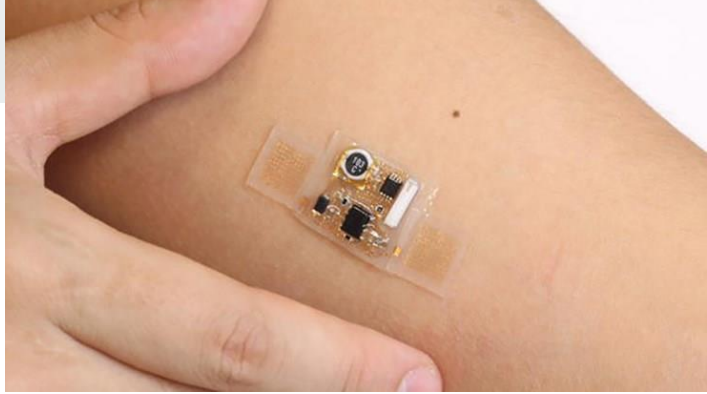
Trends: Sensors

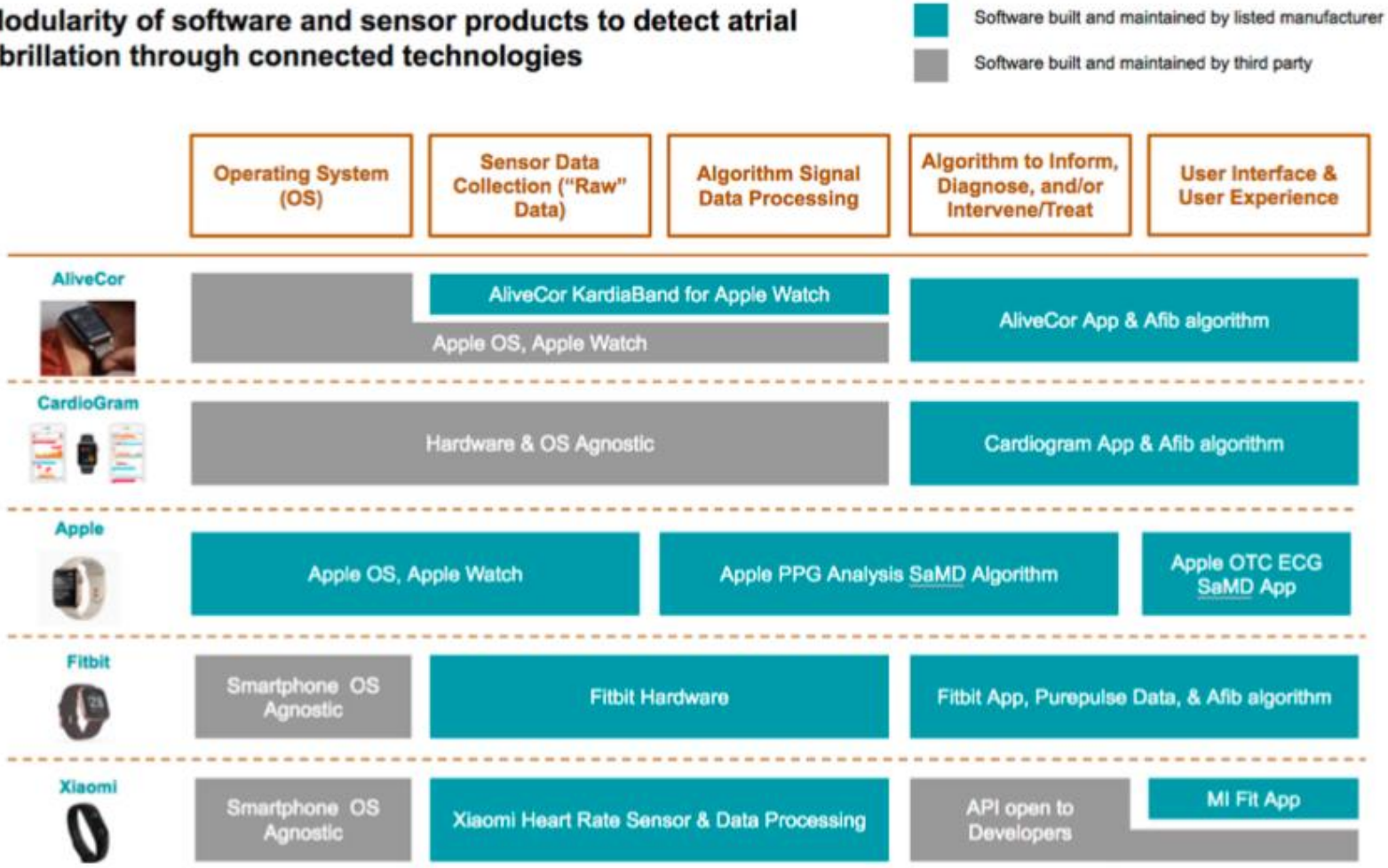


An Aptamer-based Biosensor for Troponin I Detection in Diagnosis of Myocardial Infarction

Negahdary M.[1,2], Behjati-Ardakani M.[1], Sattarahmady N.[2,3], Heli H.[2]*

Aptamer sequence	Detection Tech-niques	Trans-ducer	Detection Range	LOD	Ref
1	Electrochemilumines-cence	Gold	$8.0\times10\text{-}13^{-1}.0\times10^{-11}$ g mL^{-1}	0.3 pg mL^{-1}	(Liu et al., 2017)
2	DPV, Cyclic voltammetry	Gold	0.05-500 ng mL^{-1}	8.0 pg mL^{-1}	(Negahdary et al., 2017)
3, 4	Cyclic voltammetry, Im-pedance spectroscopy	Carbon	0.024-2.4 ng mL^{-1}	24 pg mL^{-1}	(Jo et al., 2017)
5	Impedance spectroscopy	Gold	0-10 µg mL^{-1}	0.34 µg mL-1	(Wu et al., 2010)
6-11	Square wave voltammetry	Gold	1-10 000 pmol L^{-1}	1.0 pM	(Jo et al., 2015)
12	DPV	Gold	0.03 to 2.0 ng mL^{-1}	10 pg mL^{-1}	This work

Modularity of software and sensor products to detect atrial fibrillation through connected technologies



Coravos et al.; 2019

« Not all sensors are created equal »

Table 1. Three primary application contexts for human performance devices

Application	Use cases
Wellness/Fitness	Personal health/wellness use cases, where the goal is to use data from the device to help a person to better manage their lifestyle.
	Fitness and performance use cases, where the goal is to provide data than can help to guide a training programme for sporting activity.
Healthcare	Behaviour modification use cases, where the goal is to provide input to a structured treatment programme for management of a healthcare issue, or engage patients in their own care process.
	Clinical decision-making process use cases, where the goal is to provide data that can guide diagnosis, treatment decisions or measure outcomes of care.
Clinical trials/Research	Behaviour modification use cases, where the goal is to provide input to a self-directed intervention that might compliment or enhance the impact of a therapeutic product.
	Endpoints, where the goal is to document the impact of a therapeutic product.

Caulfield et al.; 2019

Need for a validation framework

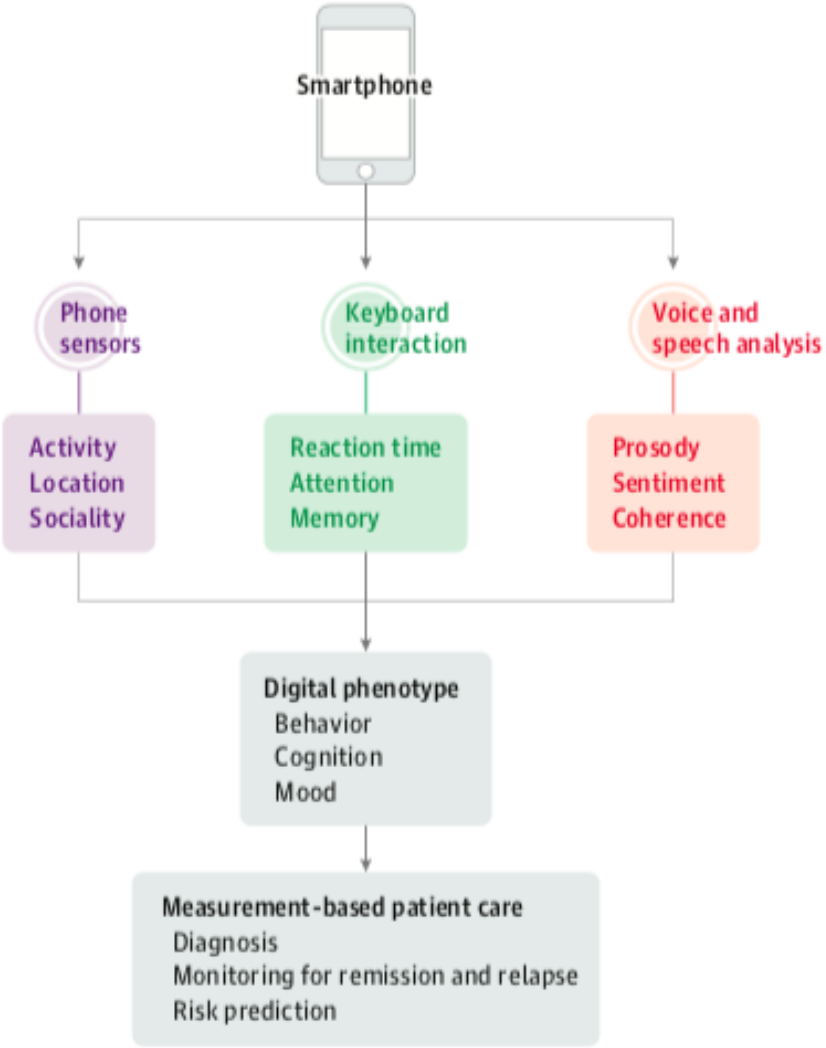
for IoT and sensors

- ★ Hardware and software

- ★ Endpoints
  - ○ Functions, features, variability
  - ○ Tests for communication layers
  - ○ Digital twins
  - ○ Tests to validate aggregate data

Trends:

Digital phenotyping



Insel et al.; 2017

Patient

Diabetologist

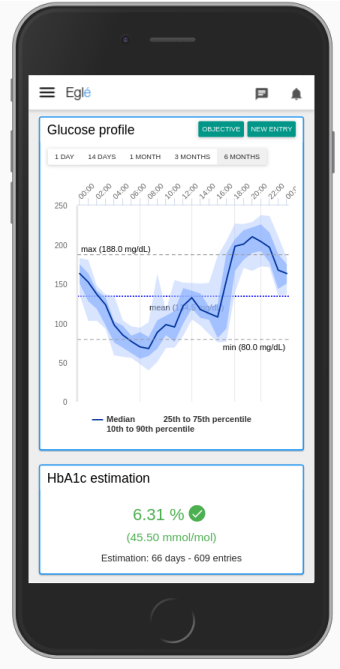
Daily monitoring

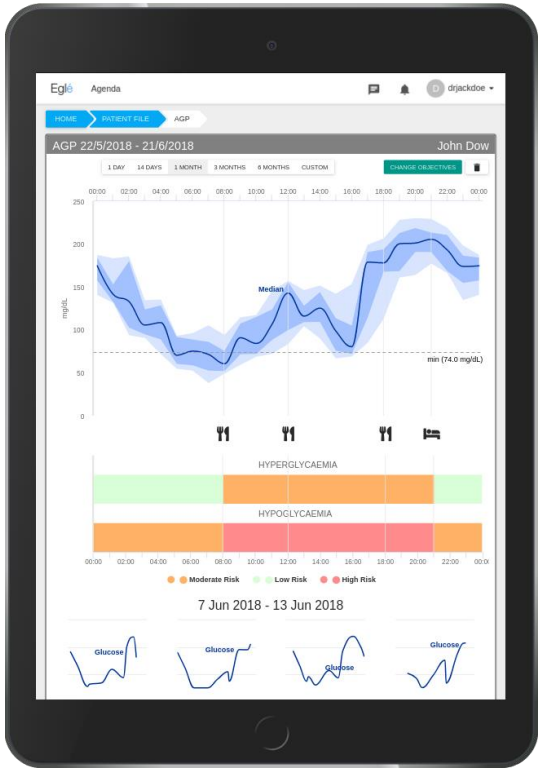
Treatment Assistant

Gamified coaching

HbA1c estimation

Chat





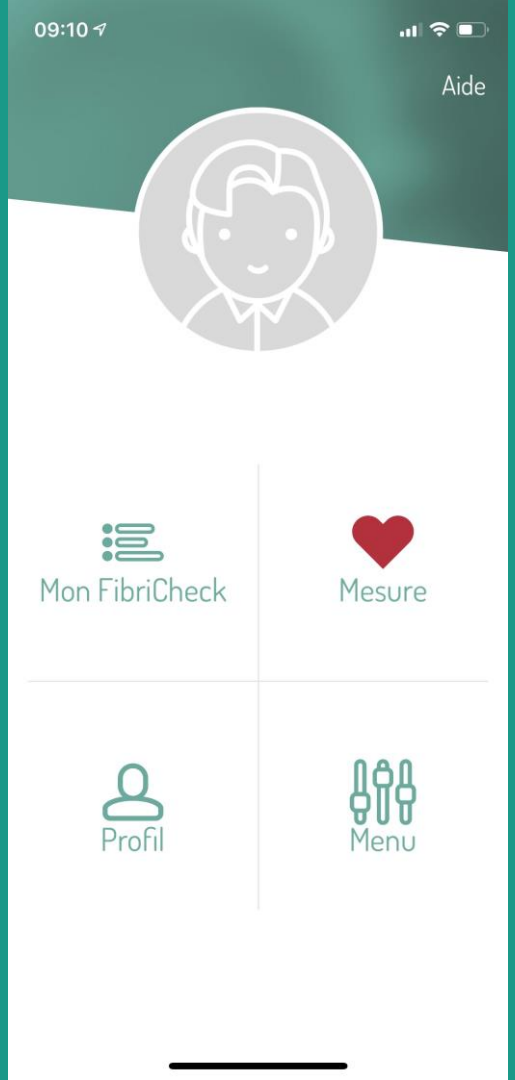
Decision support

Visualization

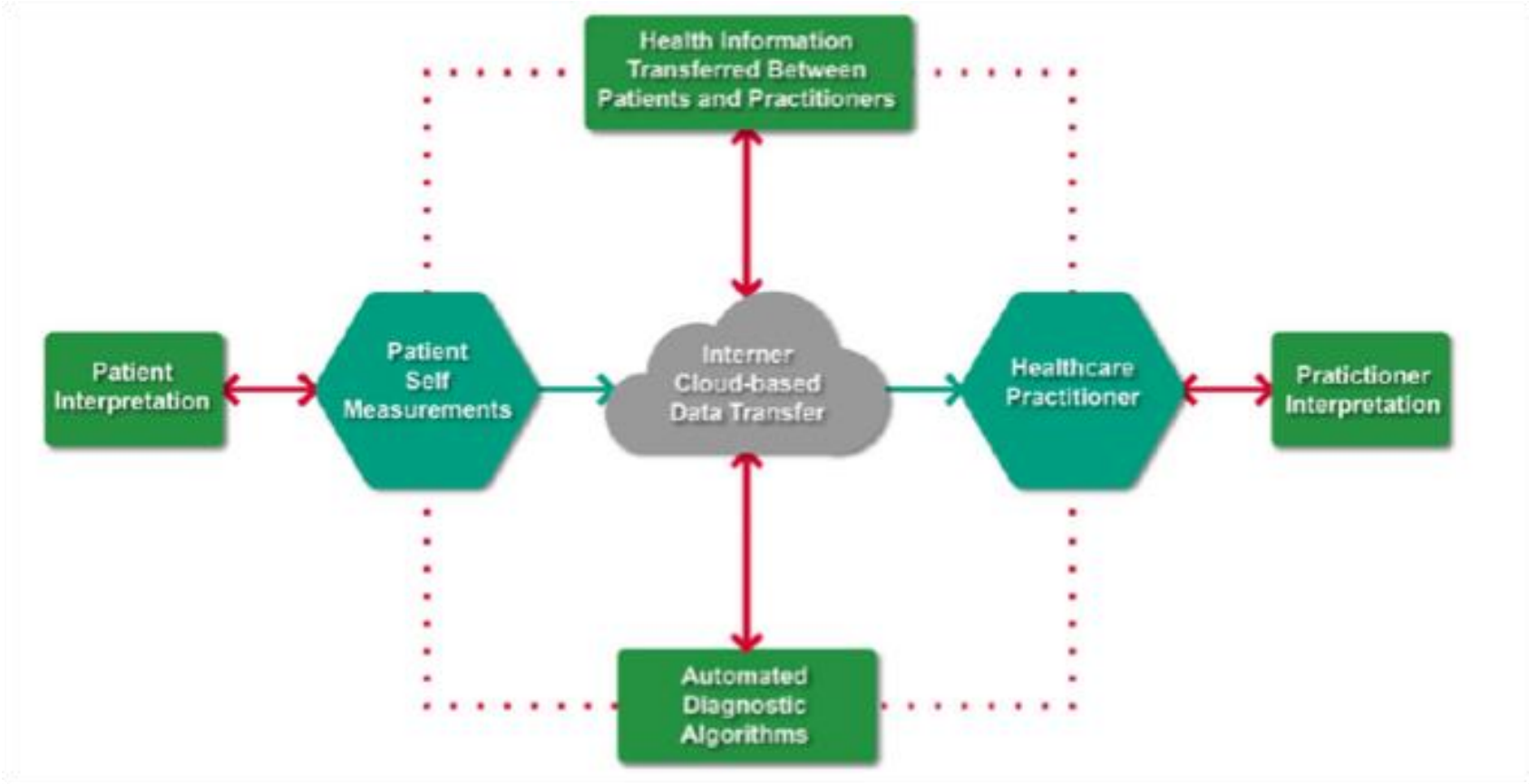
Video consulting

Appointment

Eglé - Type I diabetes Mobile application


09:10
Aide
Mon FibriCheck
Mesure
Profil
Menu


08:53
Retour
07/04/2019 - 08:51
Votre fréquence cardiaque est de...
66 BPM NORMAL
Plus d'info
Votre rythme cardiaque est ...
RÉGULIER
Plus d'info
Je ressentais...
Pas de symptôme
Confus
Vertiges
Fatigue
Palpitations
Douleur à la poitrine
Essoufflement
Autre
Je me sentais...
Stressé
Détendu
J'étais en train de...
Dormir
Etre assis
Promener
Faire de l'exercice

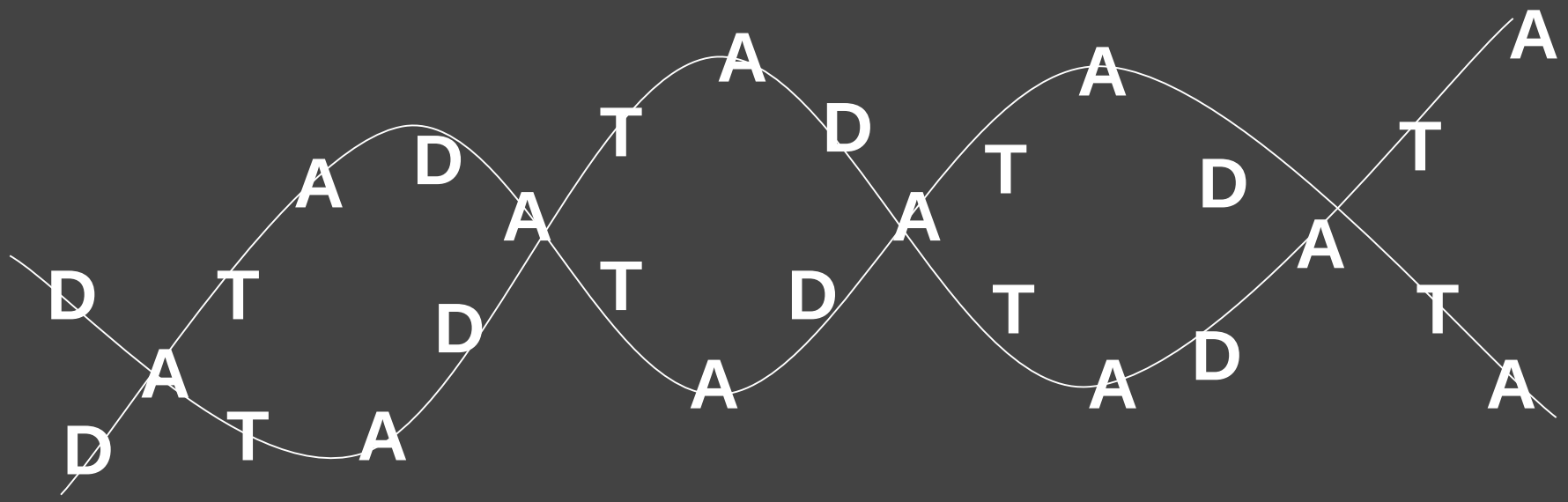


Bhavnani et al.; 2016

The power of data

Several sources

- LIS
- EMR
- Advanced imaging
- Omics
- Digital health



The processes and logistics will be integrated, intelligent and scalable

Services

Test ordering

On the road of integrated care pathways and transition care…

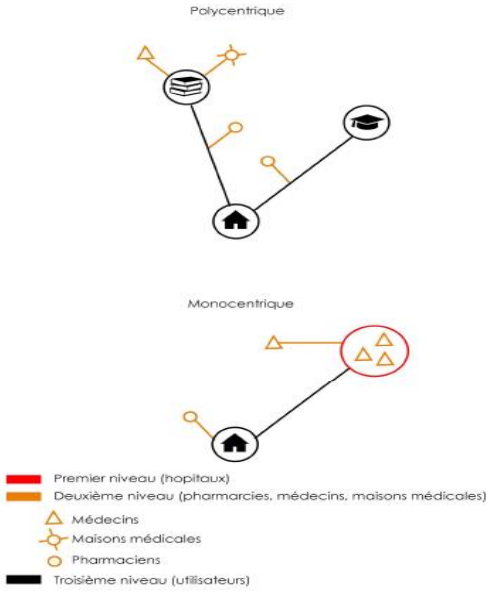
Cliniques Universitaires Saint-Luc, Brussels, Belgium

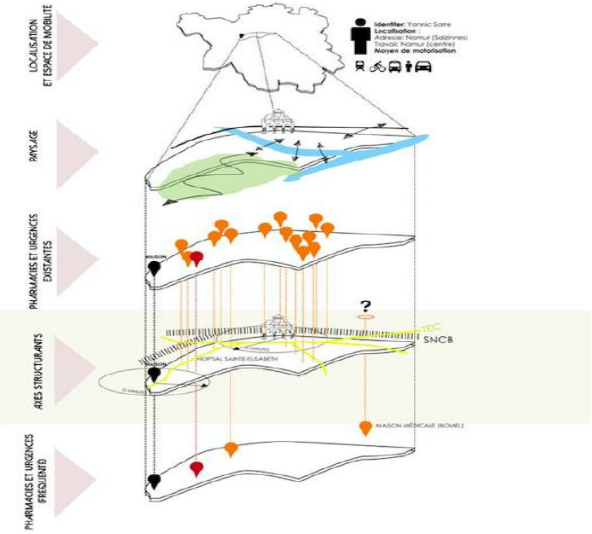
Laboratories, Tour Rosalind Franklin

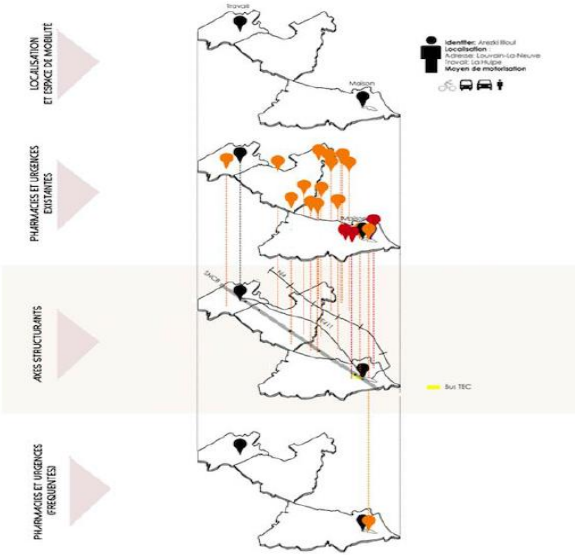
The efficient use of big data will improve operations / services

Clinical workflow

Mobility / Motility







- **Data science will provide a new set of tools that will leverage augmented laboratory medicine and will reinforce its value in a transforming healthcare ecosystem.**

- **Data science (DS) is a human-centred activity dedicated to the principled extraction of knowledge from complex data to generate insights.**

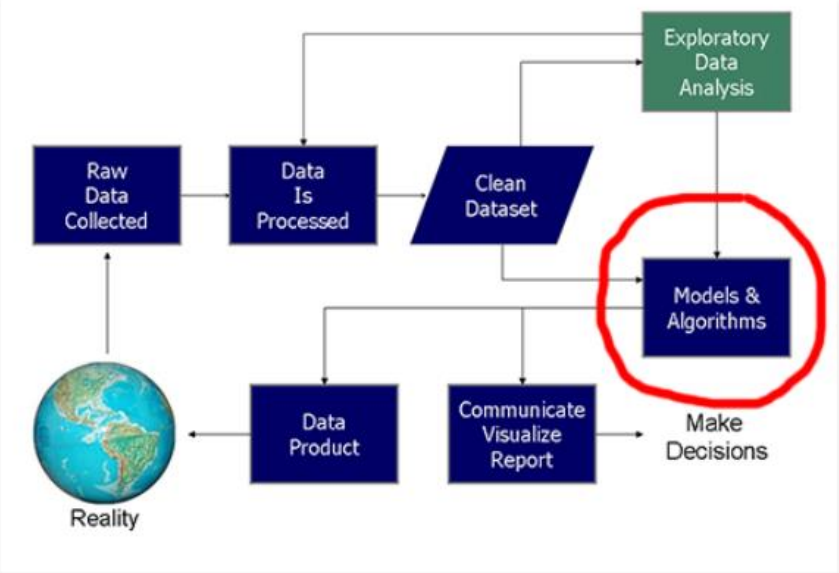
- **DS is a general field encompassing artificial intelligence (AI), but also data capture and management, advances in databases and computing infrastructures (local, distributed, Graphical Processing Units (GPU), combining conventional processors (CPU), …).**

- **Artificial intelligence (AI) is a field of computing sciences that could be encompassed in DS and devoted to mimic human thought processes and behaviours uses to make decisions or take action**

- **Machine Learning is a sub-field of AI, built upon concepts from statistics and optimization, that can be described as the development of computer programs that learn from experience (i.e. examples) with respect to some task and performance measure.**

106 STARTUPS TRANSFORMING HEALTHCARE WITH AI

Mazzanti et al.; 2018



- **Why now?**
- **Off the shelf or tailor made?**
- **Applications perspectives?**
  - **Process and care pathways**
  - **Test ordering and interpretation**
  - **Data mining, early diagnosis and proactive disease monitoring**
  - **Personalized treatment and clinical trials**
- **Positive regulation?**

  1. Patient information and consent?
  2. AI Human Warrantee ?
  3. Graduation of regulation according to the level of sensitivity of healthcare data ?
  4. Accompaniment of the adaptation of healthcare professions ?
  5. intervention of an independent external supervision ?

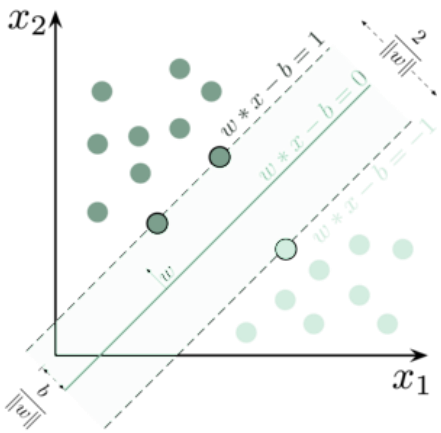
The European Commission's

HIGH-LEVEL EXPERT GROUP ON ARTIFICIAL INTELLIGENCE

AI

DRAFT
ETHICS GUIDELINES FOR TRUSTWORTHY AI

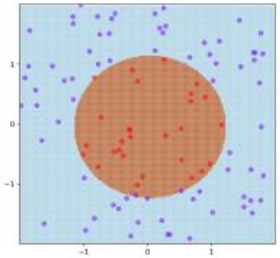
Machine Learning

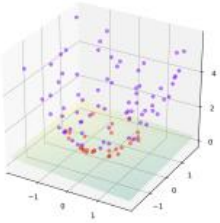


01 **Supervised vs. Unsupervised**

02 **Support Vector Machines**

03 **Balancing Data**





Using Machine Learning-Based Multianalyte Delta Checks to Detect Wrong Blood in Tube Errors

Matthew W. Rosenbaum, MD, and Jason M. Baron, MD

From the Department of Pathology, Massachusetts General Hospital, Harvard Medical School, Boston.

Key Words: Delta check; WBIT; Wrong blood in tube; Preanalytic error; Machine learning; Patient safety

Am J Clin Pathol 2018;00:1-12

Wrong blood in tube (WBIT) error.

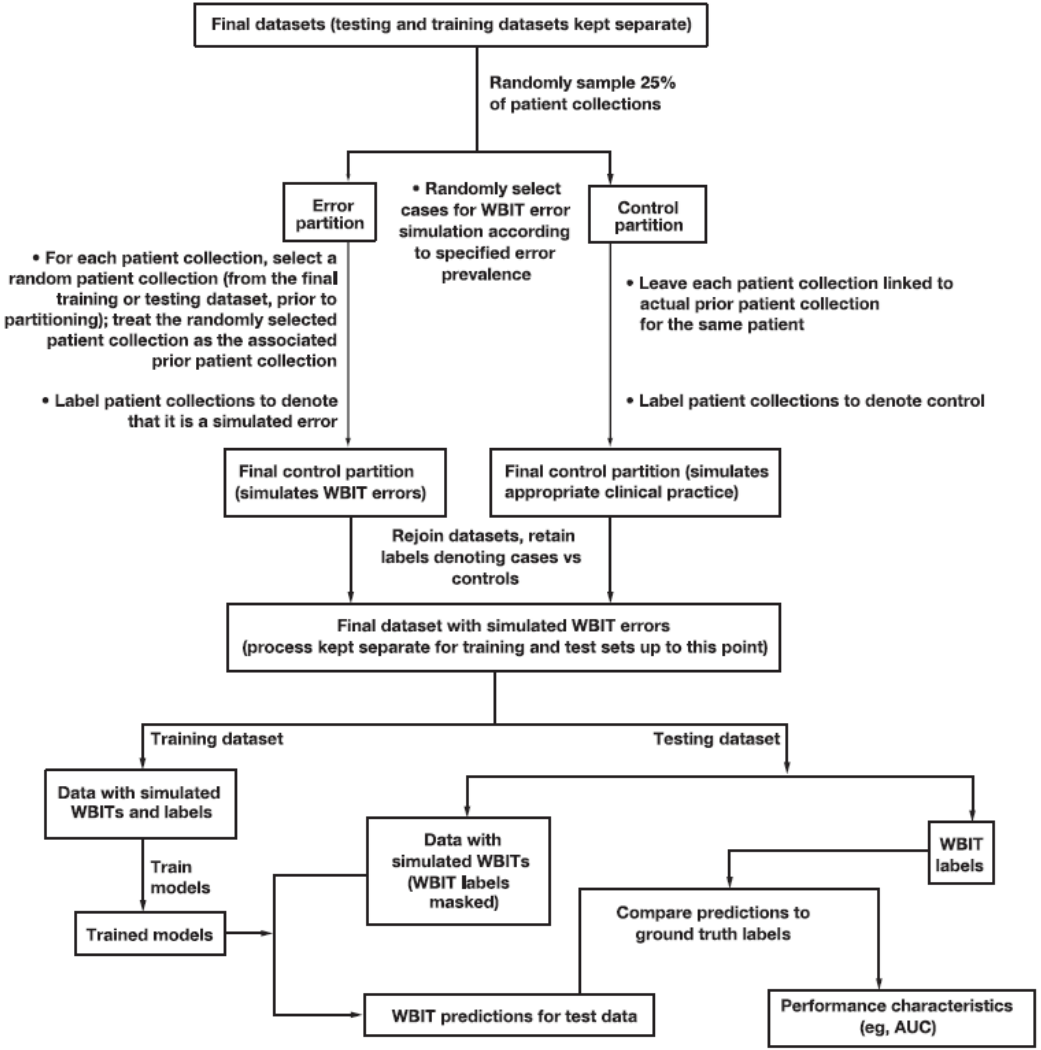
Original Data

Patient admission	Collection date/time	Na	K	...	Prior Na	Prior K	...
1234567 - 1/1/1990	1/2/1990 6 AM	140	3.9	...	--	--	
1234567 - 1/1/1990	1/3/1990 6 AM	141	3.8	...	140	3.9	
2234567 - 1/1/1990	1/2/1990 6 AM	142	3.6	...	--	--	
2234567 - 1/1/1990	1/3/1990 6 AM	143	3.7	...	142	3.6	
3234567 - 1/1/1990	1/2/1990 6 AM	131	5.1	...	--	--	
3234567 - 1/1/1990	1/3/1990 6 AM	133	5.0	...	131	5.1	

After WBIT Error Simulation

Patient admission	Collection date/time	Na	K	...	Prior Na	Prior K	...	Case/ control
1234567 - 1/1/1990	1/2/1990 6 AM	140	3.9	...	--	--		Excluded, no prior results
1234567 - 1/1/1990	1/3/1990 6 AM	141	3.8	...	140	3.9		Control
2234567 - 1/1/1990	1/2/1990 6 AM	142	3.6	...	--	--		Excluded, no prior results
2234567 - 1/1/1990	1/3/1990 6 AM	133	5.0	...	142	3.6		WBIT error case
3234567 - 1/1/1990	1/2/1990 6 AM	131	5.1	...	--	--		Excluded, no prior results
3234567 - 1/1/1990	1/3/1990 6 AM	133	5.0	...	131	5.1		Control

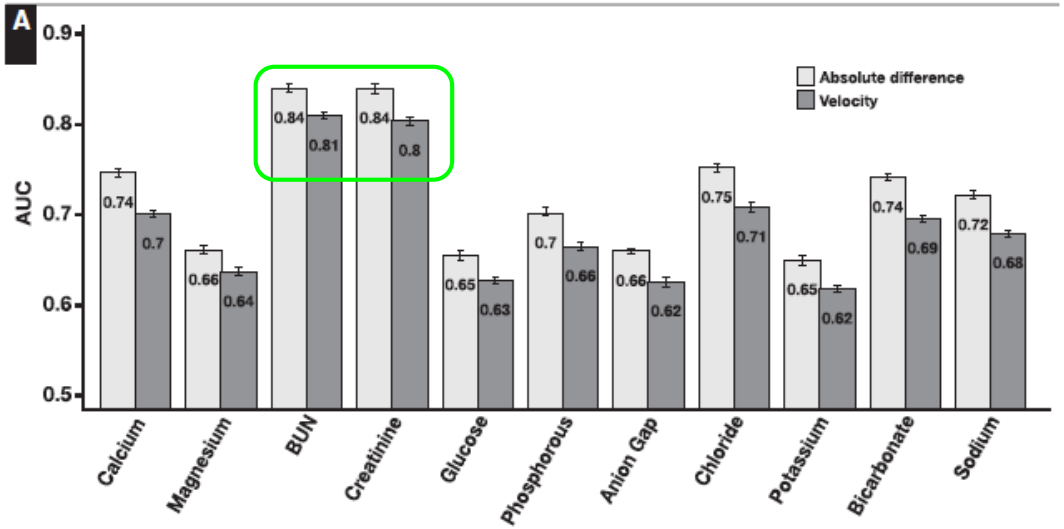
Patient 3234567 had a specimen mislabeled with a label from patient 2234567

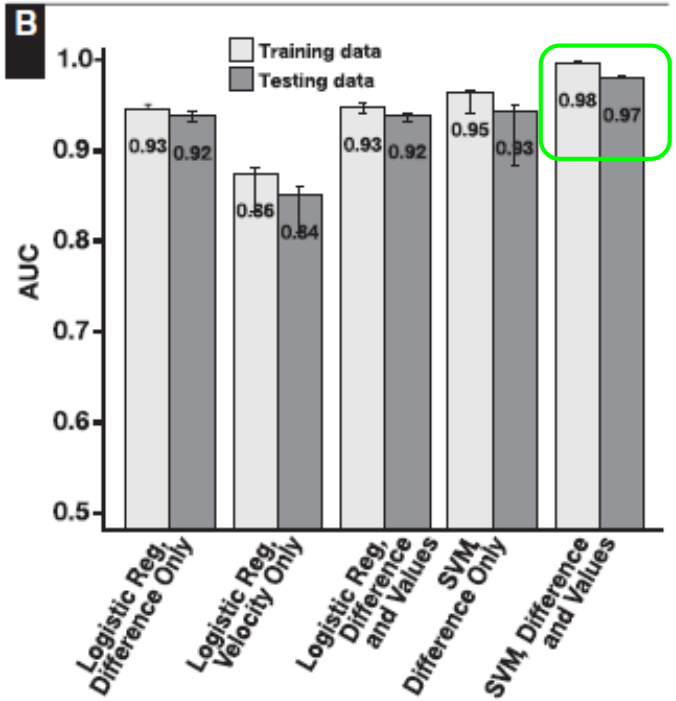

Final datasets (testing and training datasets kept separate)
Randomly sample 25% of patient collections
Error partition
• Randomly select cases for WBIT error simulation according to specified error prevalence
Control partition
• For each patient collection, select a random patient collection (from the final training or testing dataset, prior to partitioning); treat the randomly selected patient collection as the associated prior patient collection
• Label patient collections to denote that it is a simulated error
• Leave each patient collection linked to actual prior patient collection for the same patient
• Label patient collections to denote control
Final control partition (simulates WBIT errors)
Final control partition (simulates appropriate clinical practice)
Rejoin datasets, retain labels denoting cases vs controls
Final dataset with simulated WBIT errors (process kept separate for training and test sets up to this point)
Training dataset
Testing dataset
Data with simulated WBITs and labels
Train models
Trained models
Data with simulated WBITs (WBIT labels masked)
WBIT labels
Compare predictions to ground truth labels
WBIT predictions for test data
Performance characteristics (eg, AUC)

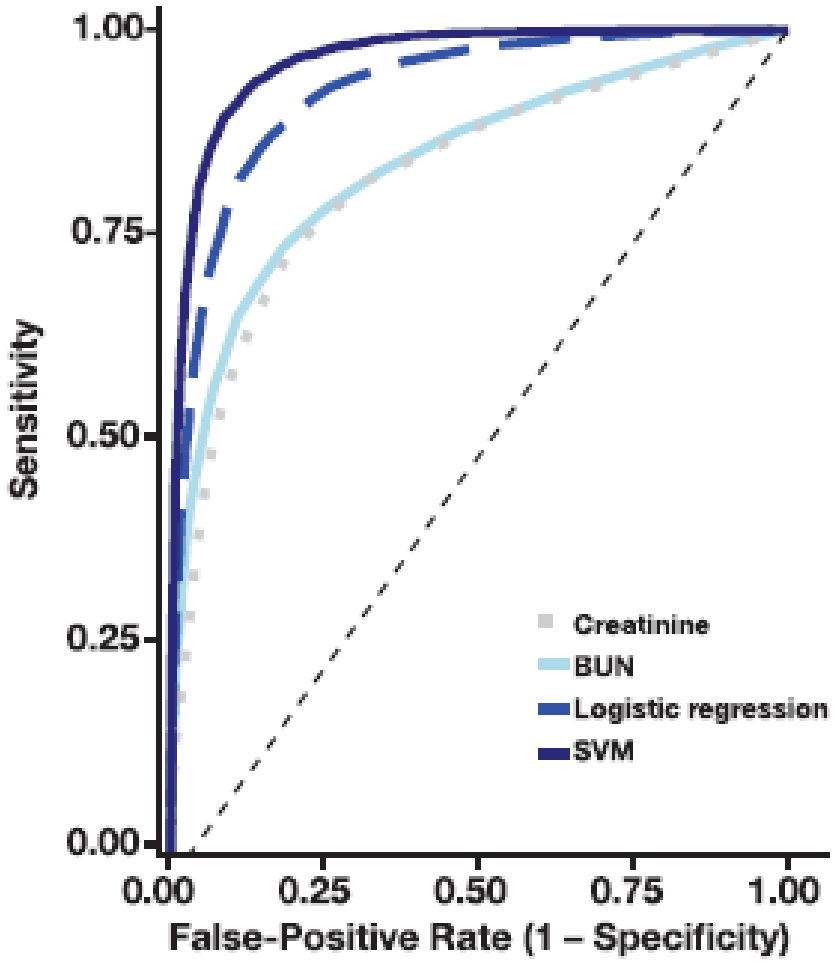
Models Used to Predict Wrong Blood in Tube Errors in This Study

Model Name	Type	Predictors
Univariate models		
Univariate absolute difference (named for each analyte)	Univariate: evaluate sensitivity/specific at various thresholds	Absolute change in consecutive results for each analyte
Univariate velocity	Univariate: evaluate sensitivity/specific at various thresholds	Absolute velocity of change between consecutive results for each analyte
Multivariate models		
Logistic regression, difference only	Logistic regression	Absolute change in consecutive results for each analyte
Logistic regression, velocity only	Logistic regression	Absolute velocity of change between consecutive results for each analyte
Logistic regression, difference and values	Logistic regression	(1) Absolute change in consecutive results for each analyte; (2) actual test results
SVM, difference only	SVM	Absolute change in consecutive results for each analyte
SVM, difference and values	SVM	(1) Absolute change in consecutive results for each analyte; (2) actual test results

SVM, support vector machines.


A
AUC
0.9
0.8
0.7
0.6
0.5
Absolute difference
Velocity
0.74
0.7
0.66
0.64
0.84
0.81
0.84
0.8
0.65
0.63
0.7
0.66
0.66
0.62
0.75
0.71
0.65
0.62
0.74
0.69
0.72
0.68
Calcium
Magnesium
BUN
Creatinine
Glucose
Phosphorous
Anion Gap
Chloride
Potassium
Bicarbonate
Sodium


B
AUC
1.0
0.9
0.8
0.7
0.6
0.5
Training data
Testing data
0.93
0.92
0.86
0.84
0.93
0.92
0.95
0.93
0.98
0.97
Logistic Reg, Difference Only
Logistic Reg, Velocity Only
Logistic Reg, Difference and Values
SVM, Difference Only
SVM, Difference and Values


1.00
0.75
0.50
0.25
0.00
Sensitivity
0.00
0.25
0.50
0.75
1.00
False-Positive Rate (1 – Specificity)
Creatinine
BUN
Logistic regression
SVM

ORIGINAL RESEARCH

American Heart Association | American Stroke Association

Machine Learning Outperforms ACC/AHA CVD Risk Calculator in MESA

Ioannis A. Kakadiaris, PhD; Michalis Vrigkas, PhD; Albert A. Yen, MD; Tatiana Kuznetsova, MD; Matthew Budoff, MD; Morteza Naghavi, MD

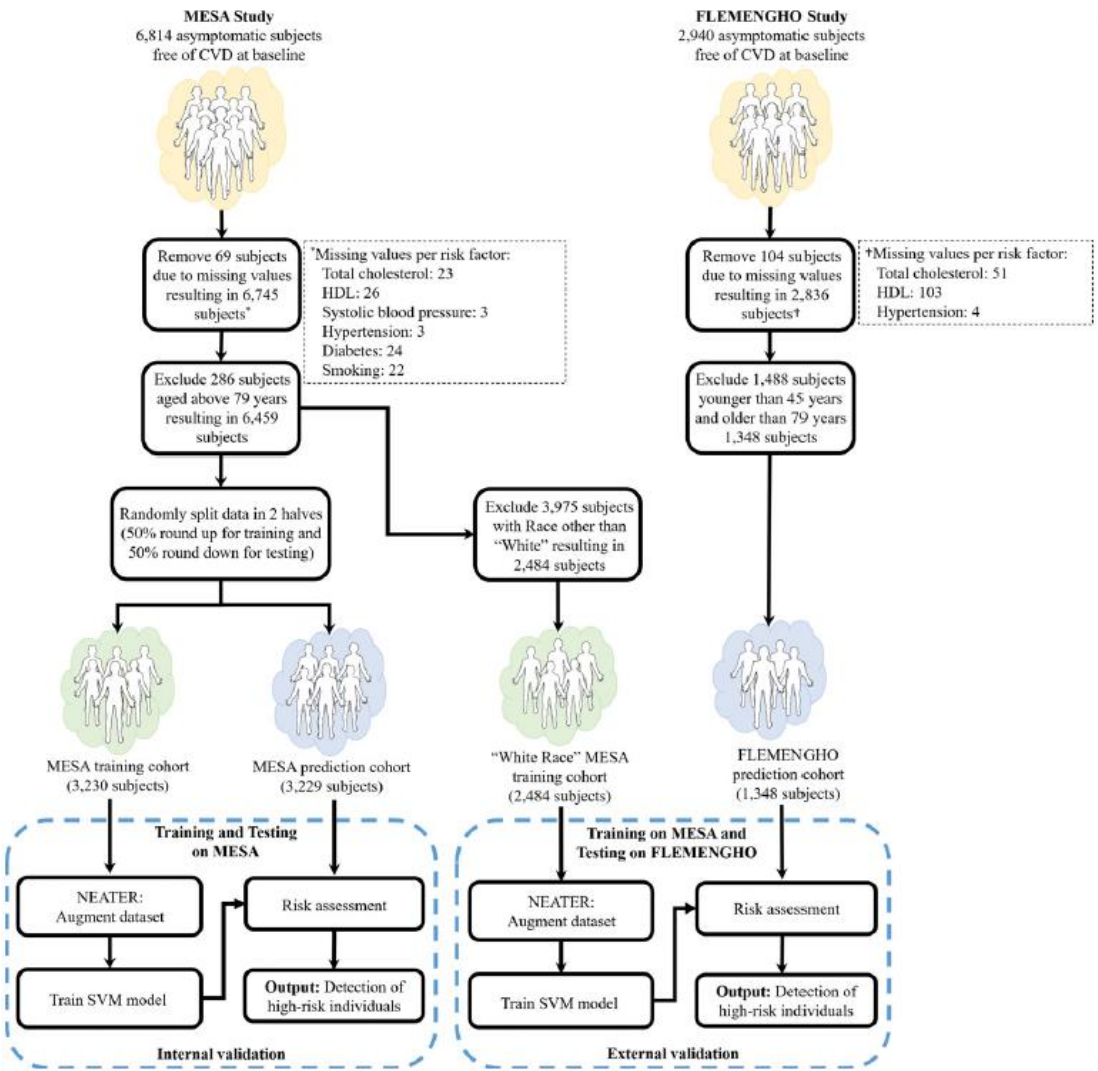
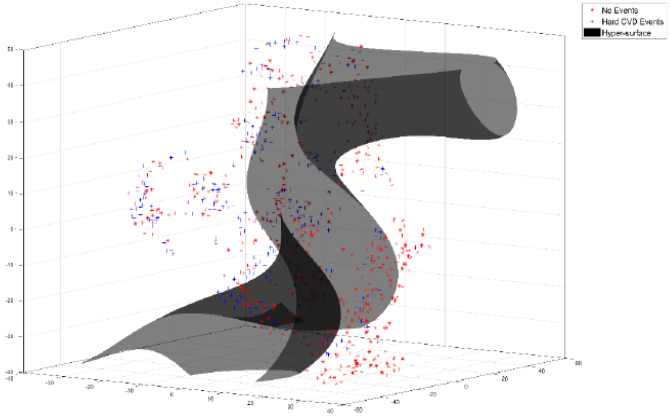
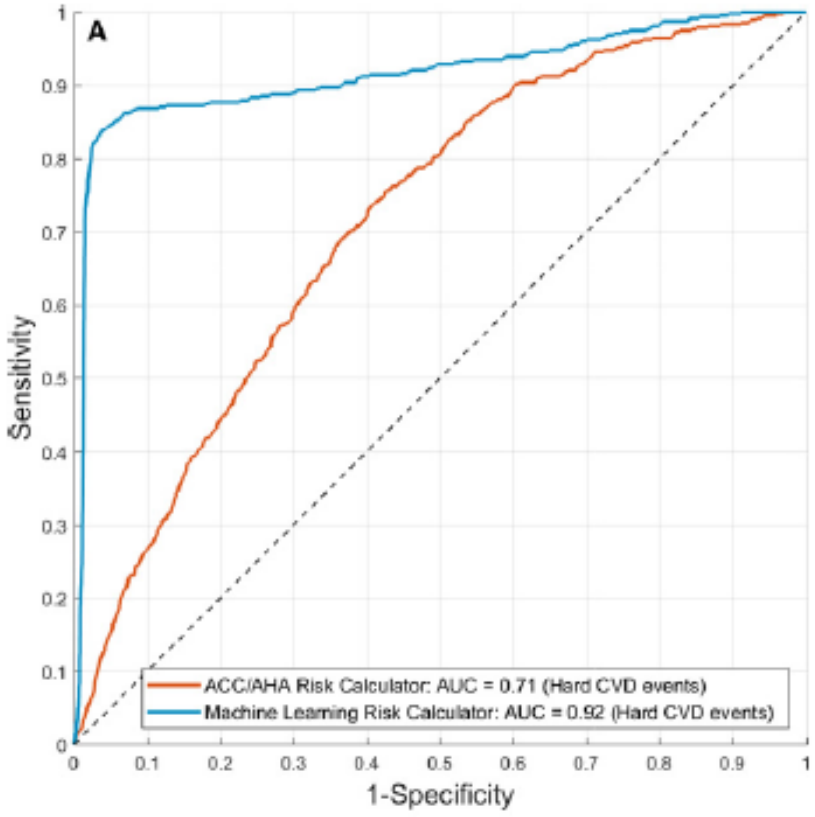
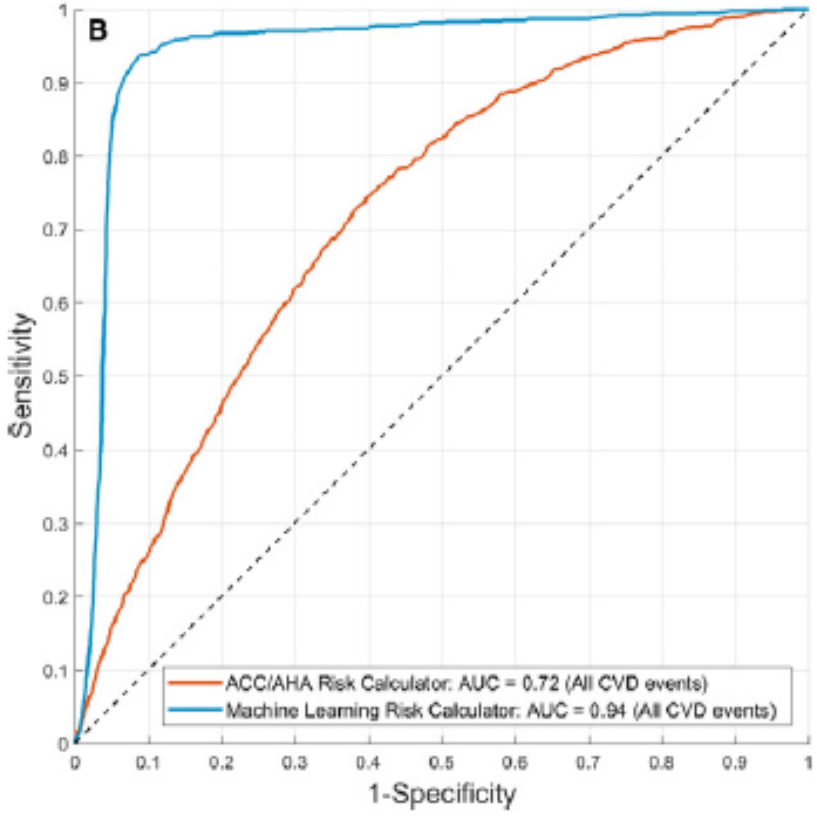

MESA Study
6,814 asymptomatic subjects free of CVD at baseline
FLEMENGHO Study
2,940 asymptomatic subjects free of CVD at baseline
Remove 69 subjects due to missing values resulting in 6,745 subjects*
*Missing values per risk factor:
Total cholesterol: 23
HDL: 26
Systolic blood pressure: 3
Hypertension: 3
Diabetes: 24
Smoking: 22
Remove 104 subjects due to missing values resulting in 2,836 subjects†
†Missing values per risk factor:
Total cholesterol: 51
HDL: 103
Hypertension: 4
Exclude 286 subjects aged above 79 years resulting in 6,459 subjects
Exclude 1,488 subjects younger than 45 years and older than 79 years 1,348 subjects
Randomly split data in 2 halves (50% round up for training and 50% round down for testing)
Exclude 3,975 subjects with Race other than "White" resulting in 2,484 subjects
MESA training cohort (3,230 subjects)
MESA prediction cohort (3,229 subjects)
"White Race" MESA training cohort (2,484 subjects)
FLEMENGHO prediction cohort (1,348 subjects)
Training and Testing on MESA
NEATER: Augment dataset
Train SVM model
Risk assessment
Output: Detection of high-risk individuals
Internal validation
Training on MESA and Testing on FLEMENGHO
NEATER: Augment dataset
Train SVM model
Risk assessment
Output: Detection of high-risk individuals
External validation

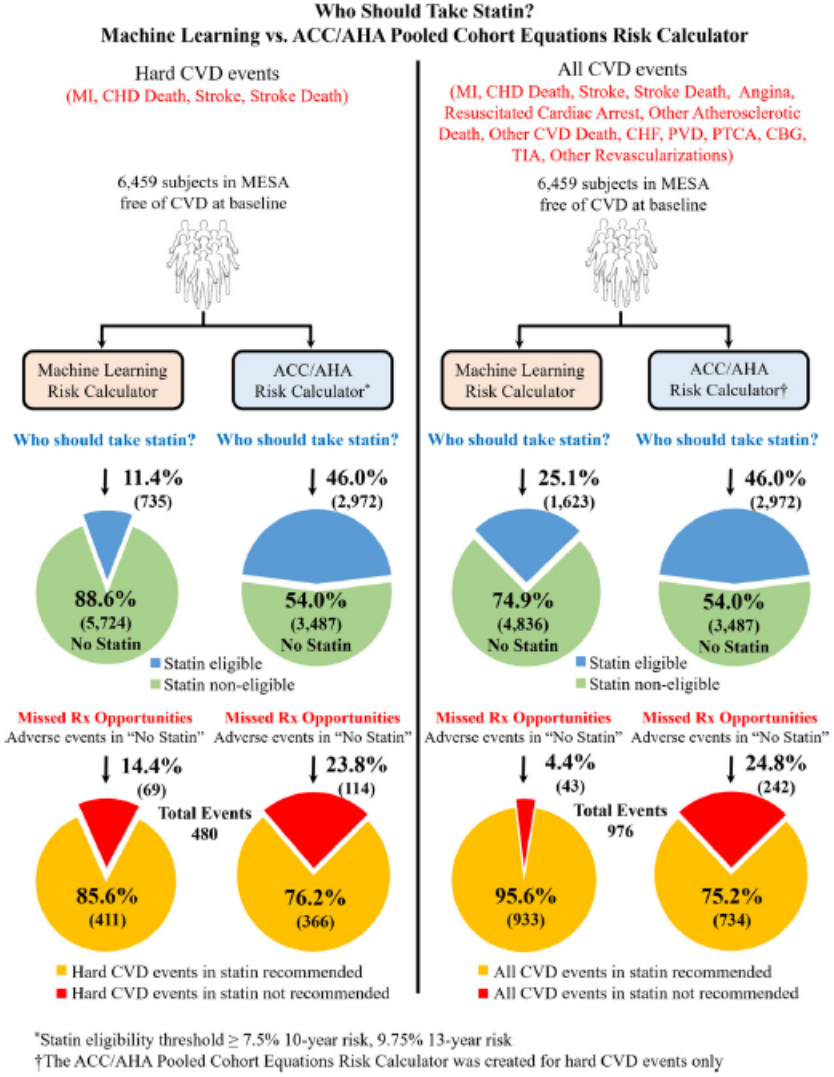
Table 2. Risk Calculator Comparison: Sensitivity-Specificity-Other Performance Metrics

Event	Model	Sn (95% CI)	*P* Value	Sp (95% CI)	*P* Value	FN	FP	TP	TN	Acc (95% CI)	*P* Value	NRI (95% CI)	*P* Value
Male													
Hard CVD	ACC/AHA Risk Calculator	0.86±0.1 (0.81–0.90)	–	0.44±0.1 (0.42–0.46)	–	40	1564	242	1214	0.48±0.1 (0.46–0.49)	–	–	–
	ML Risk Calculator	0.90±0.1 (0.86–0.94)	≤0.001	0.93±0.1 (0.92–0.94)	≤0.001	27	204	255	2574	0.92±0.1 (0.91–0.93)	≤0.001	0.53 (0.51–0.55)	≤0.001
All CVD	ACC/AHA Risk Calculator	0.84±0.1 (0.81–0.87)	–	0.47±0.1 (0.45–0.49)	–	96	1312	494	1158	0.54±0.1 (0.52–0.56)	–	–	–
	ML Risk Calculator	0.97±0.1 (0.96–0.99)	≤0.001	0.82±0.1 (0.80–0.84)	≤0.001	15	443	575	2027	0.85±0.1 (0.84–0.86)	≤0.001	0.48 (0.46–0.50)	≤0.001
Female													
Hard CVD	ACC/AHA Risk Calculator	0.63±0.1 (0.56–0.69)	–	0.67±0.1 (0.66–0.69)	–	74	1042	124	2159	0.67±0.1 (0.66–0.69)	–	–	–
	ML Risk Calculator	0.79±0.1 (0.72–0.84)	≤0.001	0.96±0.1 (0.95–0.97)	≤0.001	42	120	156	3081	0.95±0.1 (0.94–0.96)	≤0.001	0.45 (0.43–0.47)	≤0.001
All CVD	ACC/AHA Risk Calculator	0.62±0.1 (0.57–0.67)	–	0.69±0.1 (0.68–0.71)	–	146	926	240	2087	0.68±0.1 (0.67–0.70)	–	–	–
	ML Risk Calculator	0.93±0.1 (0.90–0.95)	≤0.001	0.92±0.1 (0.91–0.93)	≤0.001	28	247	358	2766	0.92±0.1 (0.91–0.93)	≤0.001	0.54 (0.52–0.55)	≤0.001
All													
Hard CVD	ACC/AHA Risk Calculator	0.76±0.1 (0.72–0.80)	–	0.56±0.1 (0.55–0.58)	–	114	2606	366	3373	0.58±0.1 (0.57–0.59)	–	–	–
	ML Risk Calculator	0.86±0.1 (0.82–0.89)	≤0.001	0.95±0.1 (0.94–0.96)	≤0.001	69	324	411	5655	0.94±0.1 (0.93–0.95)	≤0.001	0.49 (0.48–0.50)	≤0.001
All CVD	ACC/AHA Risk Calculator	0.75±0.1 (0.72–0.78)	–	0.59±0.1 (0.56–0.61)	–	242	2238	734	3245	0.62±0.1 (0.60–0.63)	–	–	–
	ML Risk Calculator	0.96±0.1 (0.94–0.97)	≤0.001	0.87±0.1 (0.86–0.88)	≤0.001	43	690	933	4793	0.89±0.1 (0.88–0.89)	≤0.001	0.50 (0.48–0.51)	≤0.001




A
Sensitivity
1-Specificity
ACC/AHA Risk Calculator: AUC = 0.71 (Hard CVD events)
Machine Learning Risk Calculator: AUC = 0.92 (Hard CVD events)


B
Sensitivity
1-Specificity
ACC/AHA Risk Calculator: AUC = 0.72 (All CVD events)
Machine Learning Risk Calculator: AUC = 0.94 (All CVD events)



Almost half of the study population (46.0%) were determined by the ACC/AHA calculator to be statin eligible.

In contrast, the ML calculator deemed only 11.4% to be at high risk and statin eligible. For "All CVD" events, the ML calculator determined 25.1% to be statin eligible.

Regarding missed treatment opportunities (false negatives), the ACC/AHA calculator also performed poorly, as 23.8% of "Hard CVD" events occurred in individuals that ACC/ AHA calculator would not have recommended statin.

The ML Risk Calculator fared better, with only 14.4% of "Hard CVD" events and only 4.4% of "All CVD" events occurring in individuals; the ML calculator would not have recommended statin.

Prediction of paroxysmal Atrial Fibrillation: A machine learning based approach using combined feature vector and mixture of expert classification on HRV signal

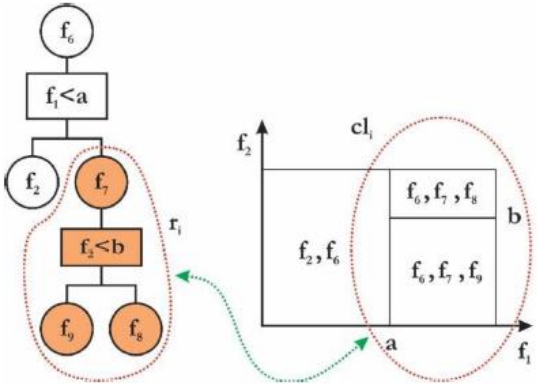


Table 6
A comparison of the presented methods in other papers and the current method, for predicting the onset of paroxysmal atrial fibrillation.

Author and year	Signal length (Min)	Feature extraction	Performance evaluation method	SEN (%)	SPE(%)	ACC (%)
Boon et al. 2016 [29]	15	HRV features	10-fold CV	77.4	81.1	79.3
Boon et al. 2018 [33]	10	HRV features	10-fold CV	58.5	81.1	68.9
Yang and Yin, 2001 [21]	10	HRV based footprint analysis	Single Hold	_	_	57.0
Hickey and Heneghan, 2002 [28]	10	Spectral based HRV features	5-fold CV	53.0	80.0	70.0
Boon et al. 2018 [33]	5	Spectral based HRV features	5-fold CV	51.0	79.0	68.0
Boon et al. 2018 [33]	5	HRV features	10-fold CV	86.8	88.7	87.7
Zong et al. 2001 (18)	30	Number and timing of PACs	Single Hold	79	_	80.0
Hickey et al. 2002 [28]	30	PACs detection and spectral based HRV features	5-fold CV	79.0	72.0	72.0
Thong et al. 2004 [19]	30	PACs analysis	Single Hold	89.0	91.0	90.0
Costin et al. 2013 [30]	30	HRV features and morphological variability of QRS complexes	Single Hold	89.3	89.4	89.4
Mohebbi et al. 2012 [31]	30	HRV features	Single Hold	96.2	93.1	94.5
Cheskonov 2008 [32]	30	HRV based spectral features	Single Hold	72.7	88.2	80.0
Lynn and Chiang [20]	30	HRV based return map and Poincare Plot features	Single Hold	_	_	64.0
The proposed method	5	HRV features	10-fold CV	100	95.5	98.2

Note: CV: Cross validation

Ebrahimzadeh et al.; 2018

Distributed learning

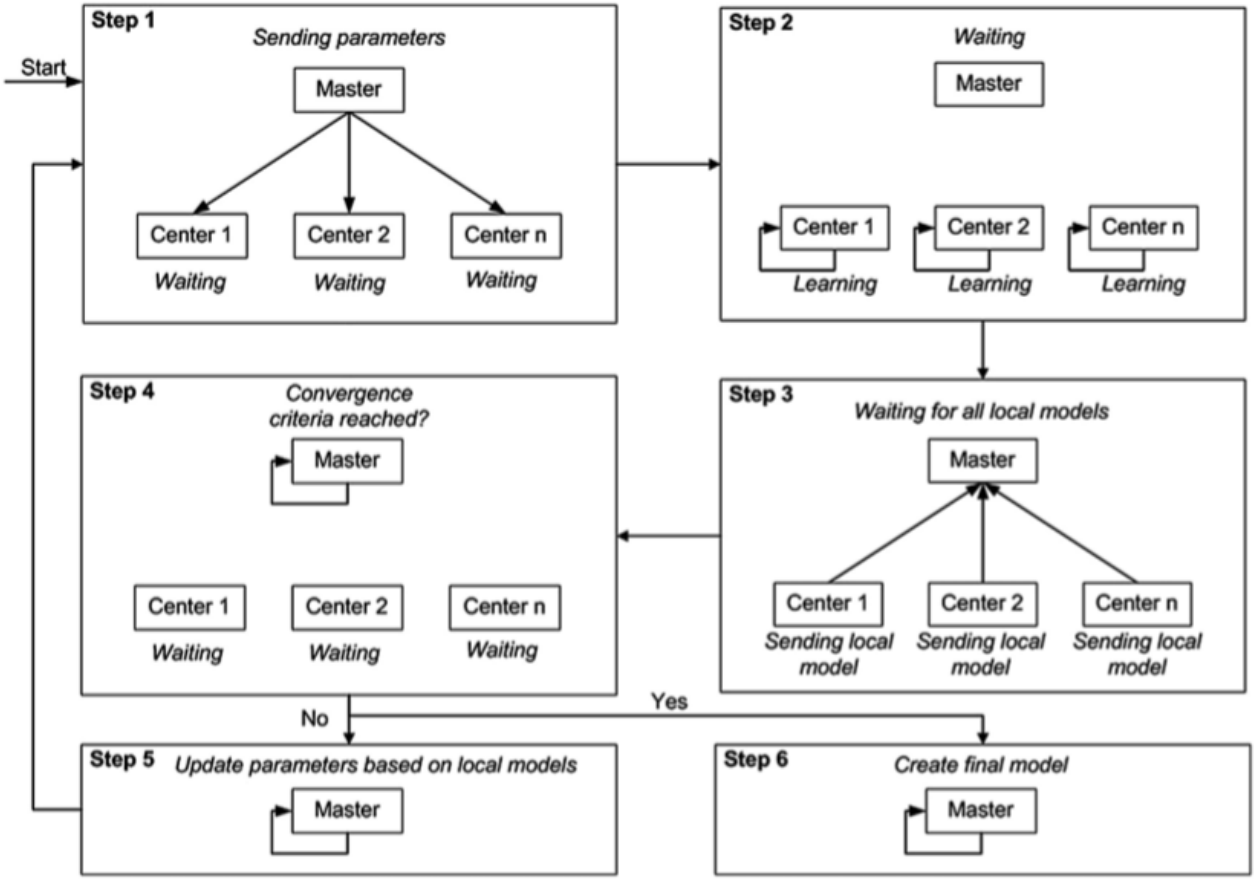
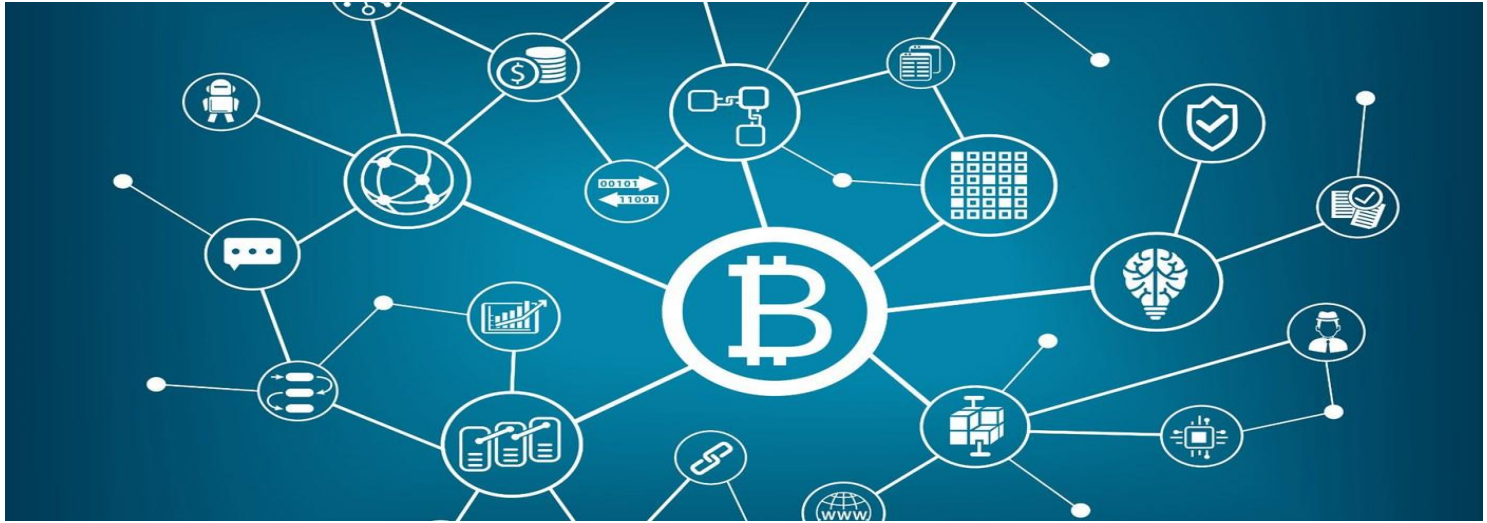


Fig. 1. Distributed learning flow in euroCAT.

Deist et al.; 2017

Relying on cloud computing and blockchain to improve accessibility, security and safety



Using avatars…

Education

« When a heart attack is suspected, timely medical treatment is critical for survival »

The SAVE app

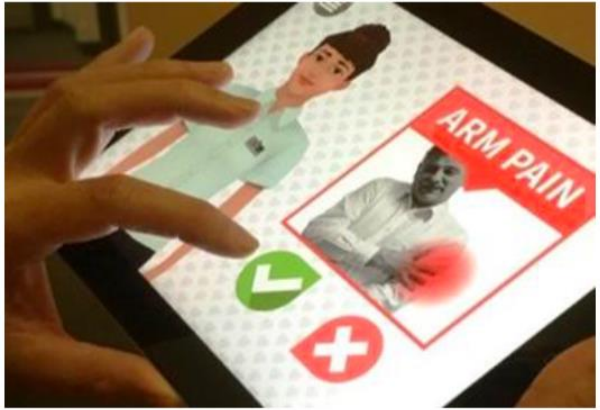
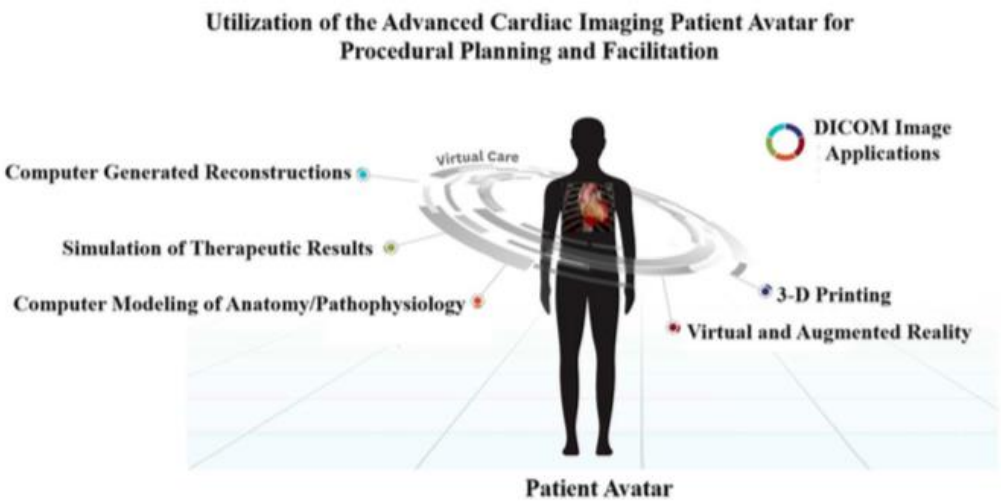


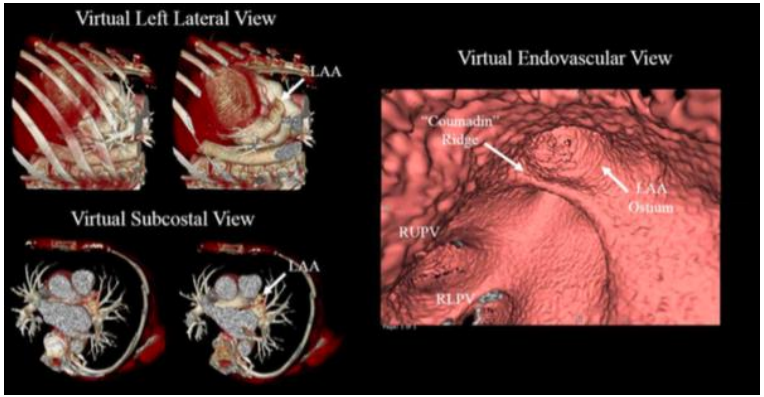
Figure 1 The screen picture of 'SAVE app'

Tongpeth et al.; 2019

Evaluation

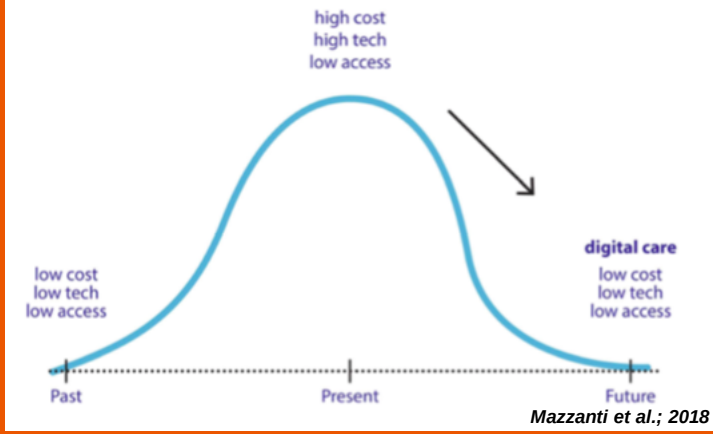
Utilization of the advanced cardiac imaging patient avatar for procedural planning and facilitation



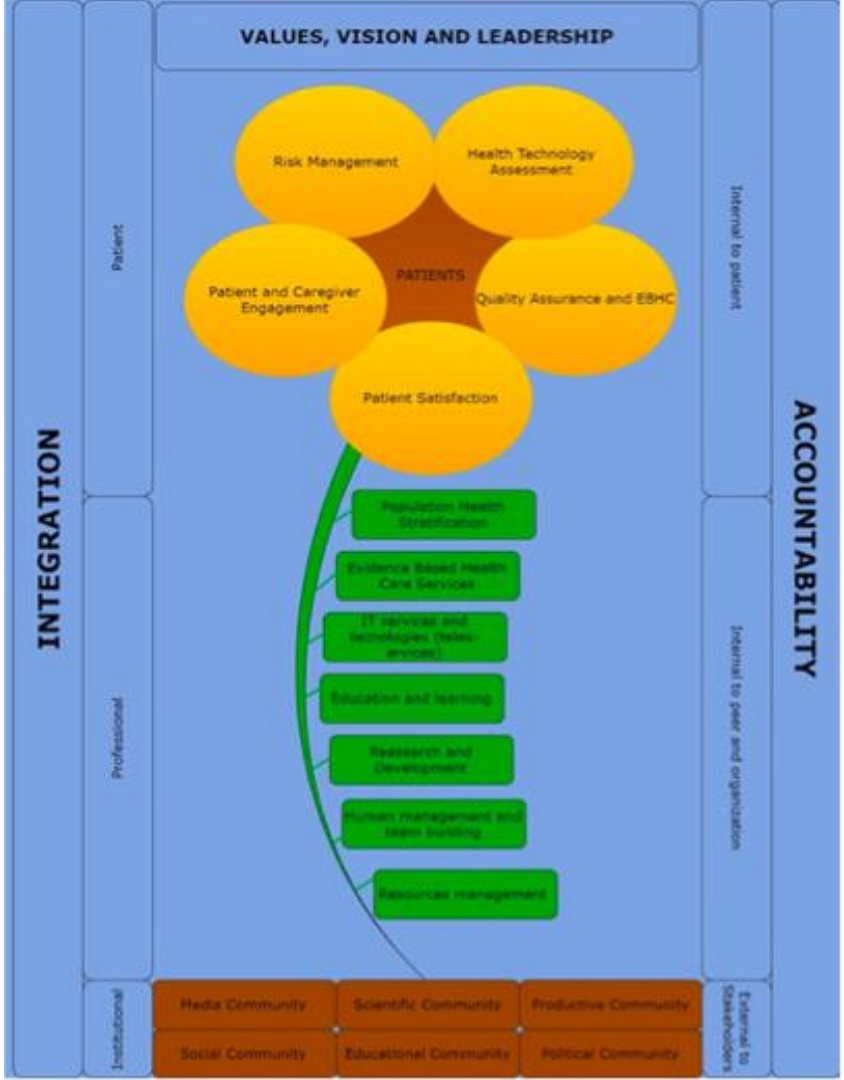


Shinbane et al.; 2017

- ✓ **Cost-effectiveness? Financing?**
- ✓ **Legal framework?**
- ✓ **Interaction between human and remote services**



Mazzanti et al.; 2018



Buja et al.; 2018

- ✓ **Innovation >< science of implementation**

(rate of development of new technologies

Vs.

preparedness of the system)?

The future is:

Us…

with the help of technology

Thank you!

damien.gruson@uclouvain.be