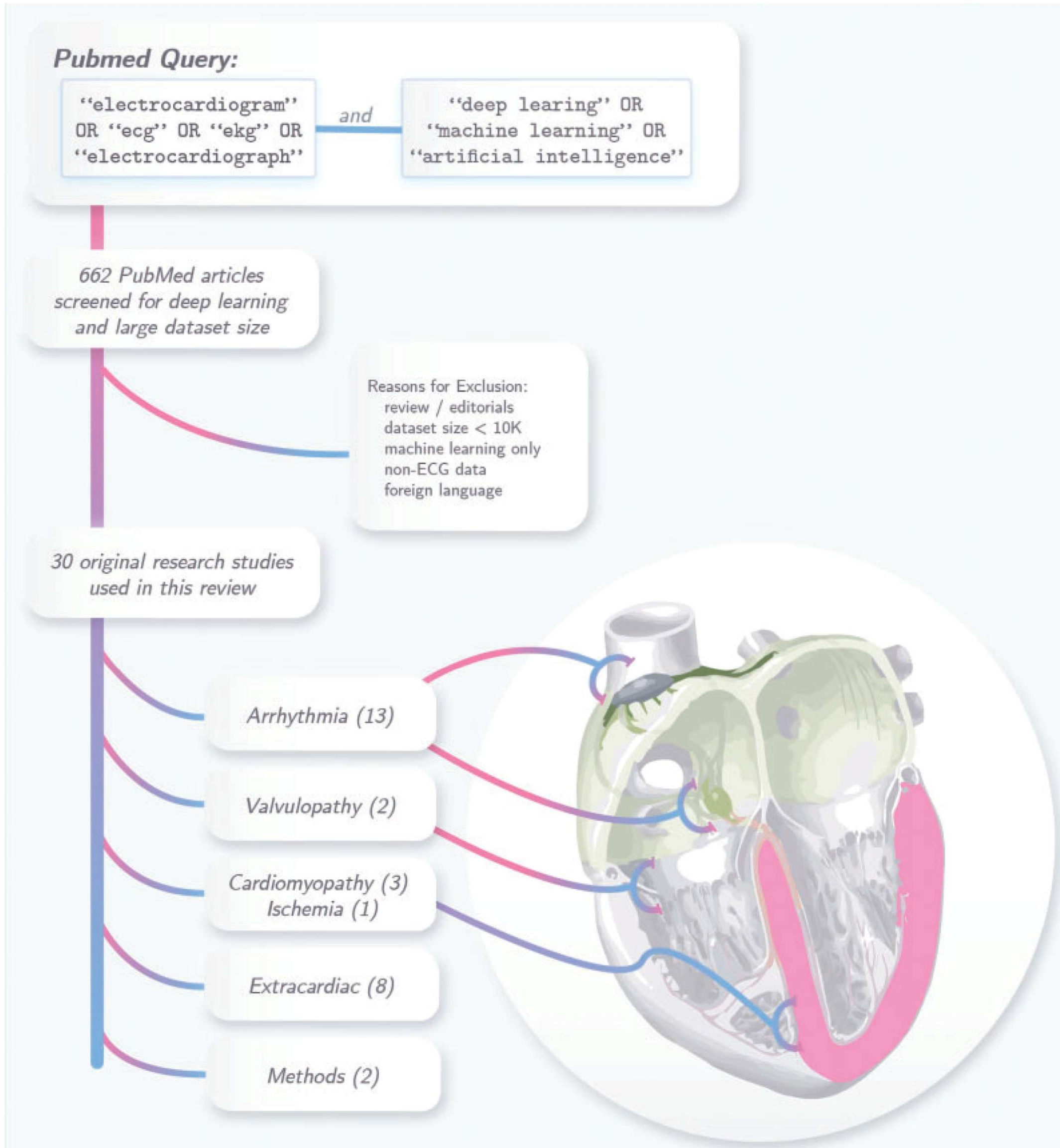
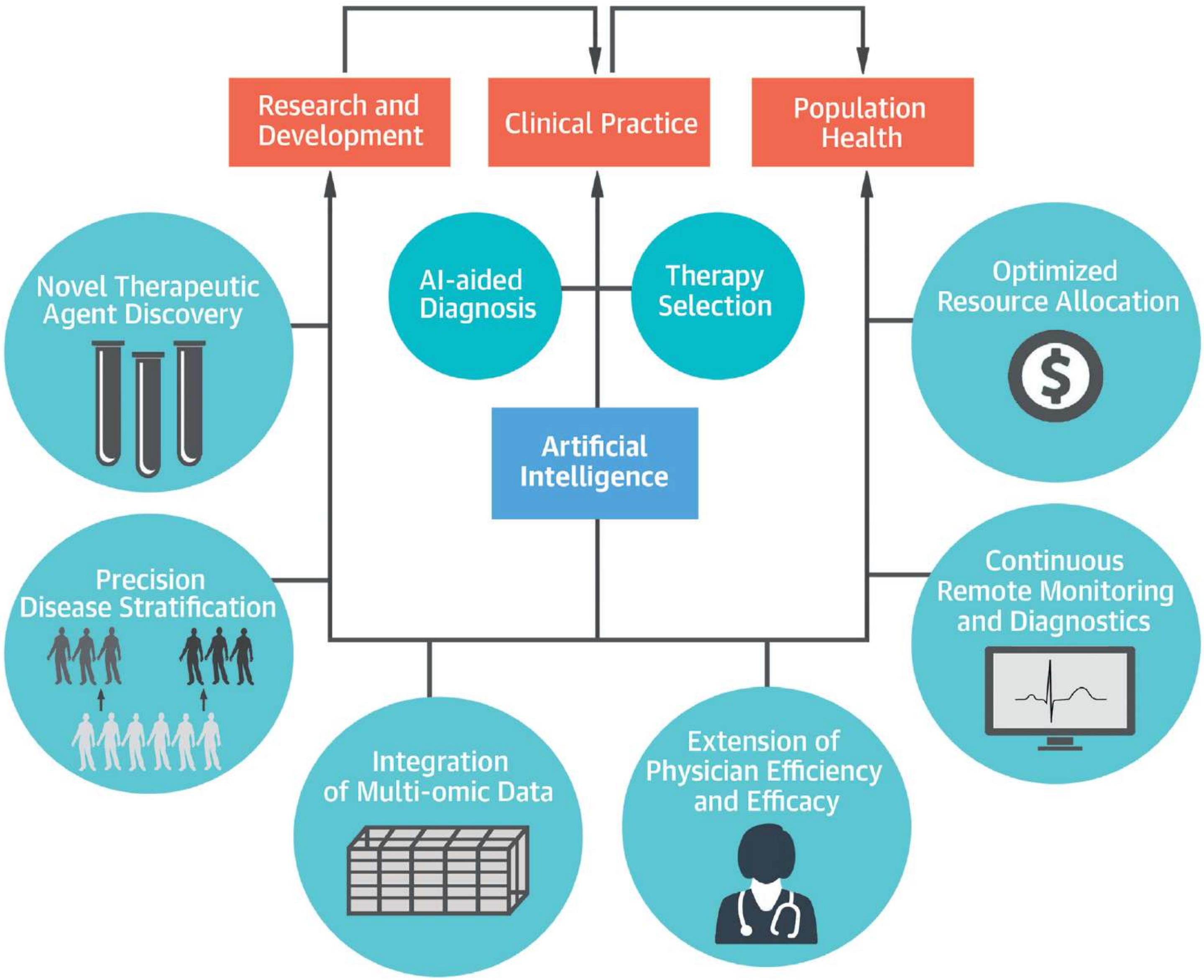
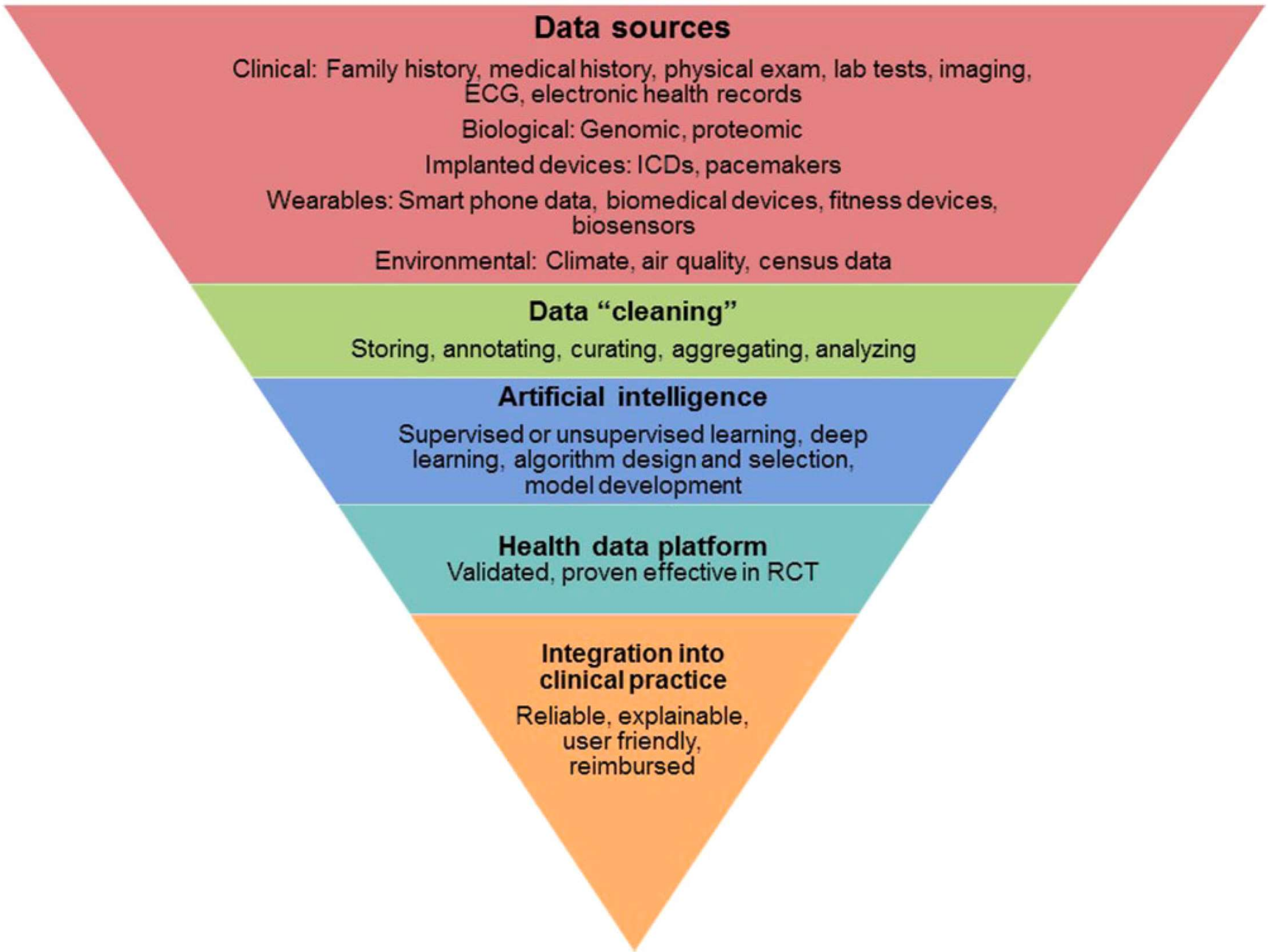
L’aritmologia clinica sotto la lente dell’intelligenza artificiale

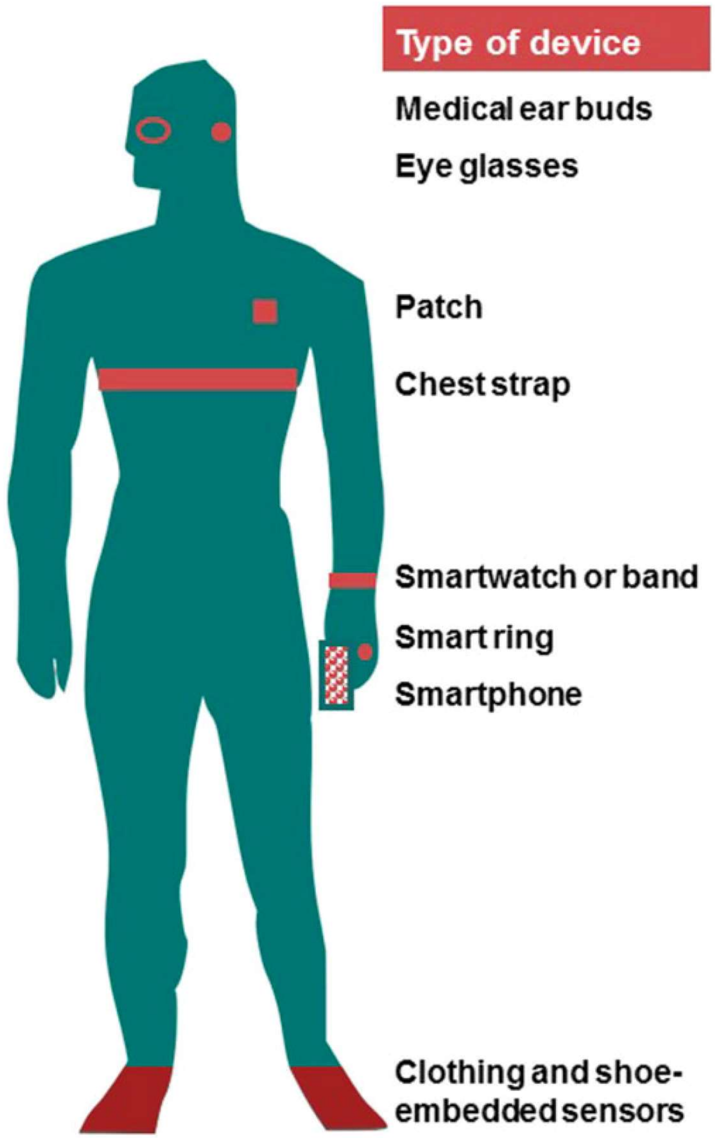
Leonardo Calò
(Policlinico Casilino, Roma)


Pubmed Query:
“electrocardiogram” OR “ecg” OR “ekg” OR “electrocardiograph”
and
“deep learing” OR “machine learning” OR “artificial intelligence”
662 PubMed articles screened for deep learning and large dataset size
Reasons for Exclusion:
review / editorials
dataset size < 10K
machine learning only
non-ECG data
foreign language
30 original research studies used in this review
Arrhythmia (13)
Valvulopathy (2)
Cardiomyopathy (3)
Ischemia (1)
Extracardiac (8)
Methods (2)



Research and Development
Clinical Practice
Population Health
Novel Therapeutic Agent Discovery
AI-aided Diagnosis
Therapy Selection
Optimized Resource Allocation
Artificial Intelligence
Precision Disease Stratification
Continuous Remote Monitoring and Diagnostics
Integration of Multi-omic Data
Extension of Physician Efficiency and Efficacy


Data sources
Clinical: Family history, medical history, physical exam, lab tests, imaging, ECG, electronic health records
Biological: Genomic, proteomic
Implanted devices: ICDs, pacemakers
Wearables: Smart phone data, biomedical devices, fitness devices, biosensors
Environmental: Climate, air quality, census data
Data "cleaning"
Storing, annotating, curating, aggregating, analyzing
Artificial intelligence
Supervised or unsupervised learning, deep learning, algorithm design and selection, model development
Health data platform
Validated, proven effective in RCT
Integration into clinical practice
Reliable, explainable, user friendly, reimbursed



Sensors	Measurements
Accelerometer **Barometer** **GPS**	Activity (e.g., step/stair counts, exercise), estimated calories burned
PPG	HR, HRR, HRV, cuff-less BP, SaO2, cardiac output, stroke volume, pulse-based rhythm detection, sleep and its stages
ECG	Single- and multi-lead ECG, continuous or as-needed monitoring, interval measurements (e.g., QTc), arrhythmia detection, electrolyte abnormalities
Oscillometer	Wrist cuff BP
Biochemical sensors	Invasive: blood glucose and electrolyte monitoring Non-invasive: sweat and saliva electrolytes and hydration status

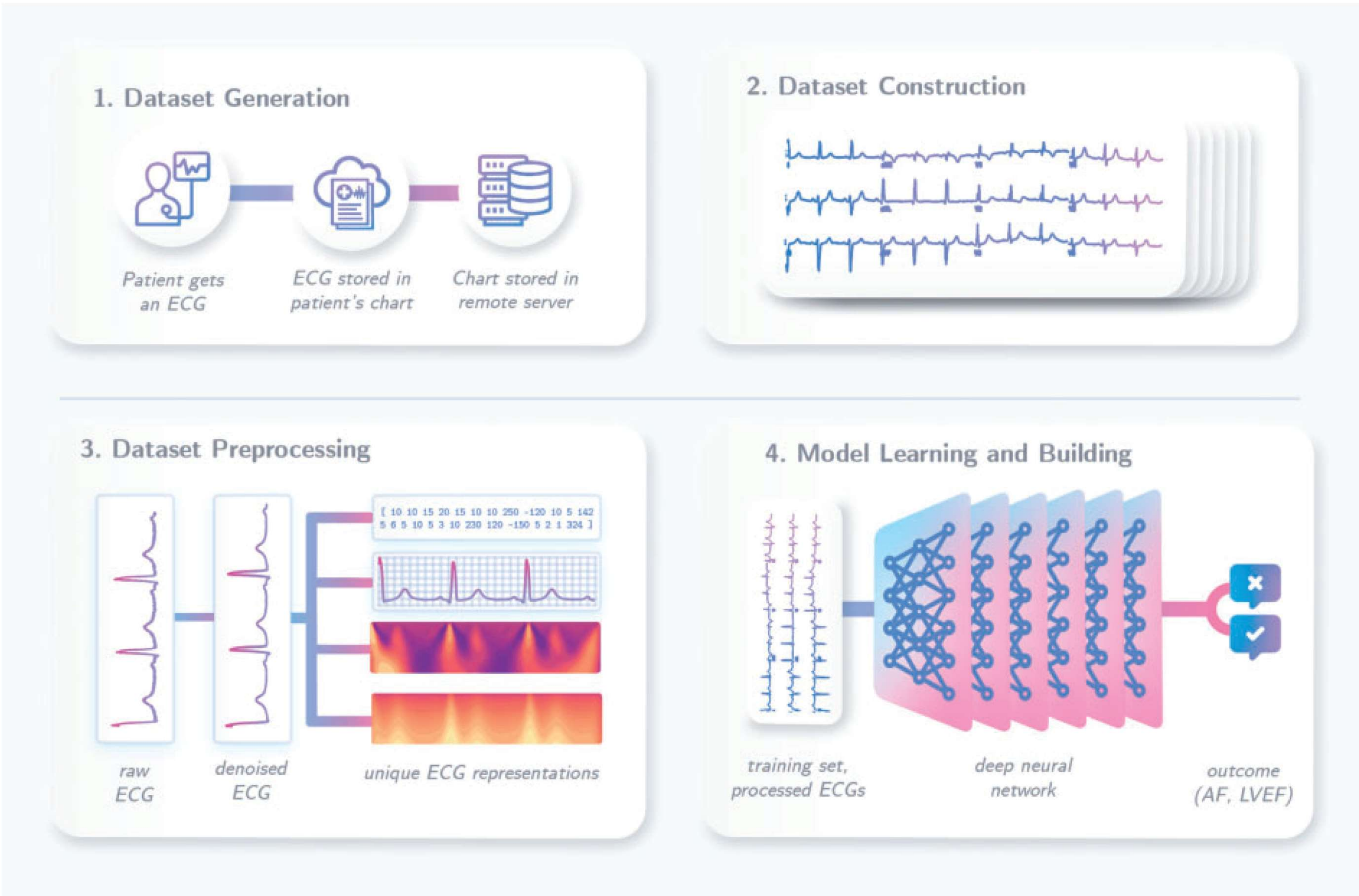
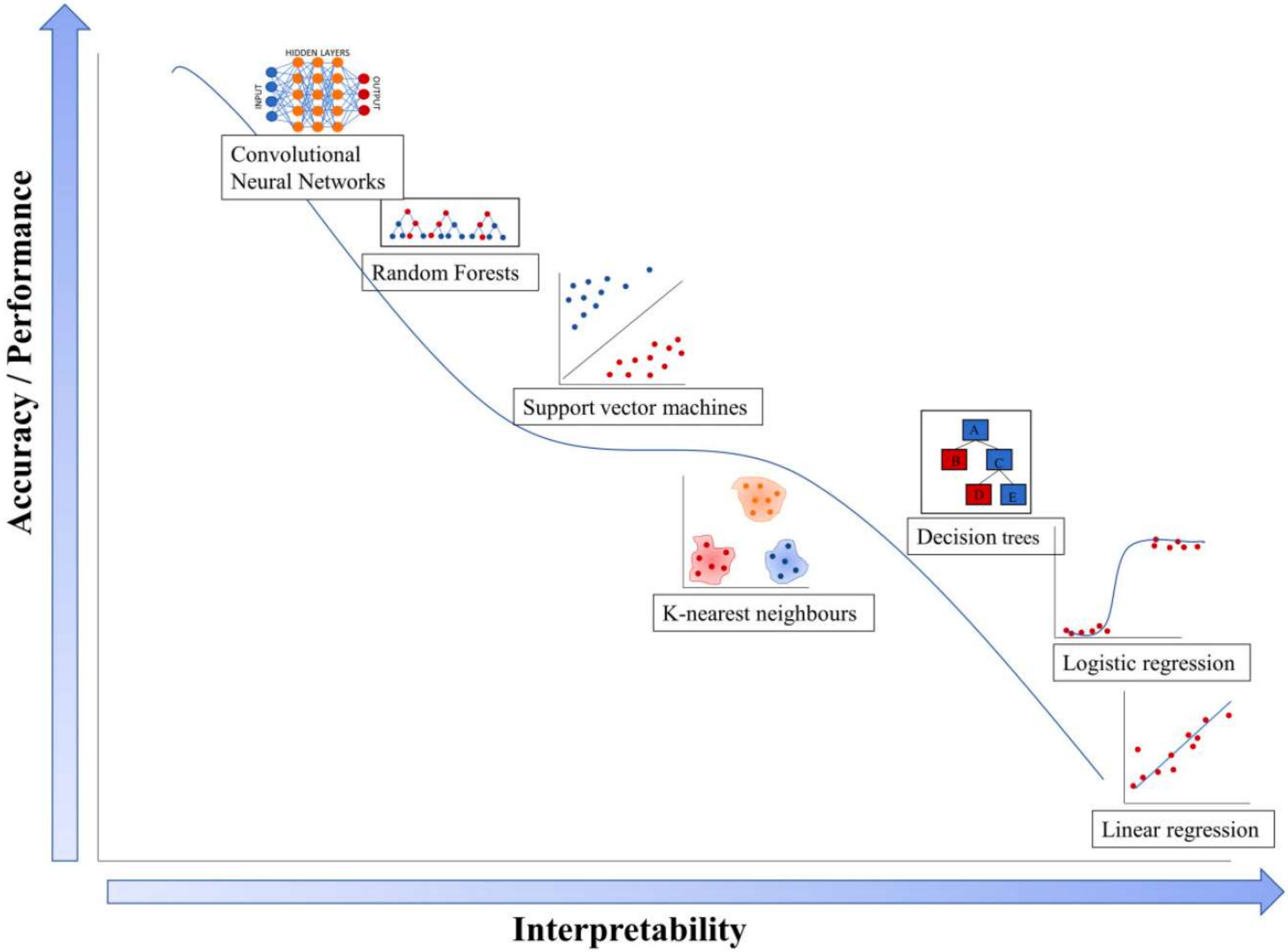
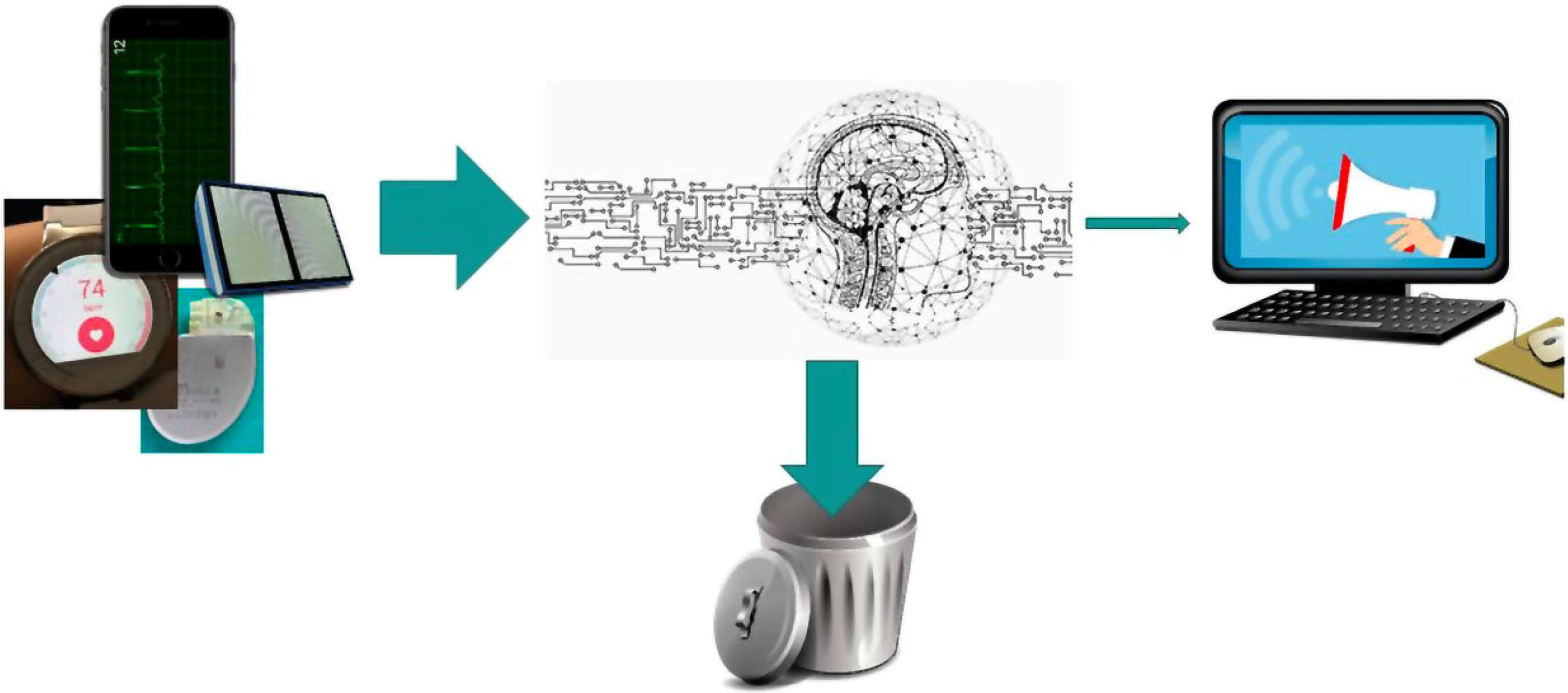

1. Dataset Generation
Patient gets an ECG
ECG stored in patient's chart
Chart stored in remote server
2. Dataset Construction
3. Dataset Preprocessing
[10 10 15 20 15 10 10 250 -120 10 5 142
5 6 5 10 5 3 10 230 120 -150 5 2 1 324]
raw ECG
denoised ECG
unique ECG representations
4. Model Learning and Building
training set, processed ECGs
deep neural network
outcome (AF, LVEF)

Table 2 Commonly used machine learning classification algorithms

Algorithm	Learning method	Description	Utility in EP ML
Support vector machine	• Most commonly used supervised learning method	• Used to classify complex non-linear data • Creates 'hyperplane' that non-linearly separates the two classes in a feature space • Good classification and generalization properties	• Arrhythmia classification using heart rate variability • VF detection algorithm in automated external defibrillators
Random Forest	• Supervised learning method	• Ensemble learning methods that combine multiple decision trees (algorithms) • Decision trees arranged in a hierarchical manner • Final prediction derived by calculating the mean or mode of the individual DT's decision	• Classification of ECG beats • CRT outcomes prediction
Bayesian networks	• Supervised learning method	• Graphical structures to represent knowledge about an uncertain domain • Represent variables and their probabilistic relationships • HMM—one of the frequently used examples of BNs	• Classification of ECG beats • CRT outcomes prediction
Neural networks	• Can be supervised or unsupervised learning method	• Computational model mimicking biological neural networks • Data is propagated in a hierarchical manner via nodes in each layer • Input/target pairs are used during model training	• Classifying large amounts of data • Classification of ECG beats
Convolutional neural networks	• Can be supervised or unsupervised learning method	• Evolved form of deep neural networks (multiple hidden layers between input and output) • Convolution layers produce a spatially dependent feature for the subsequent layer • Most widely used DL	• For deciphering diseased state footprints in 12-lead ECG • Cardiac imaging



Accuracy / Performance
HIDDEN LAYERS
INPUT
OUTPUT
Convolutional Neural Networks
Random Forests
Support vector machines
K-nearest neighbours
A
B
C
D
E
Decision trees
Logistic regression
Linear regression
Interpretability


12
74

DIGITAL HEALTH IN CARDIOLOGIA: DALL’HOLTER AI «MOBILE DEVICE»

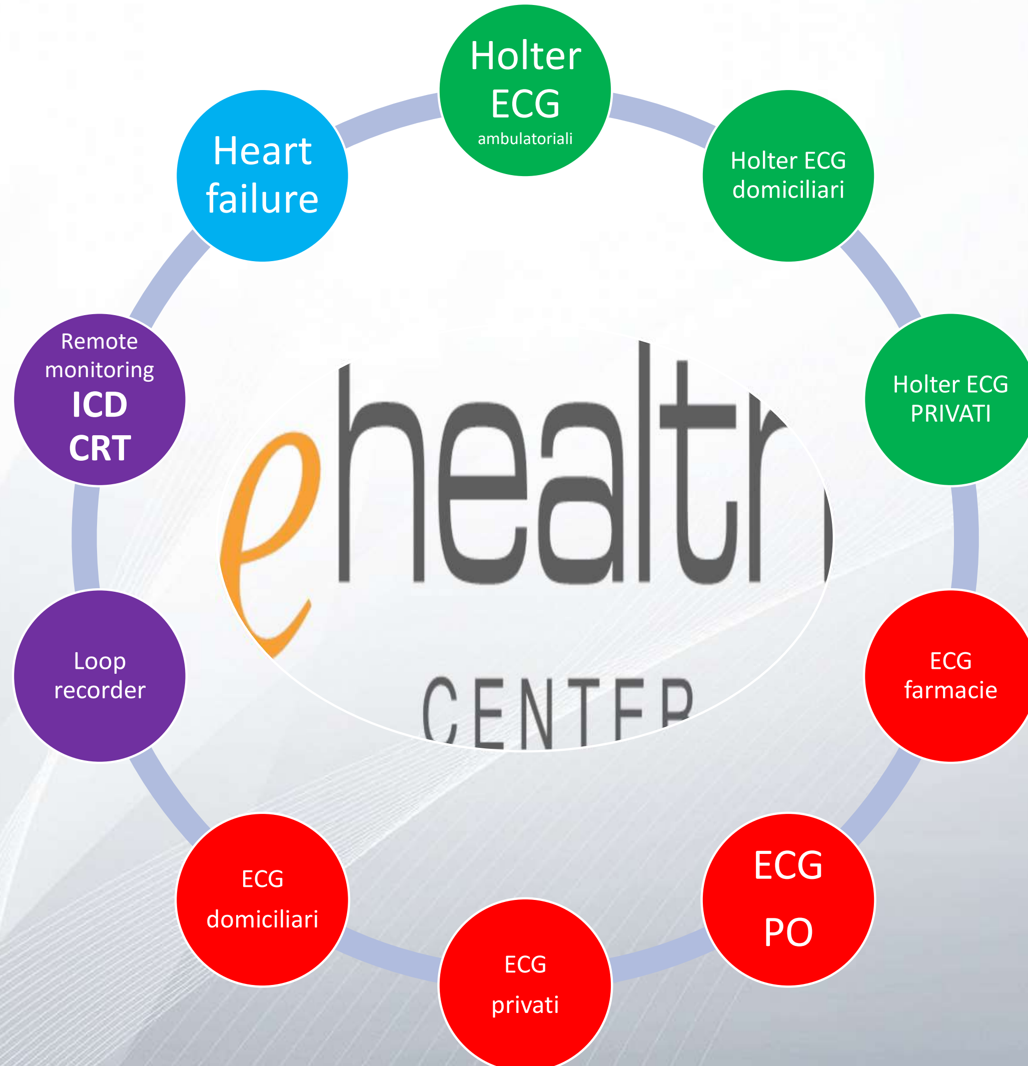
PAZIENTI E CAREGIVERS

REPARTO e AMBULATORIO CARDIOLOGIA

Preospedalizzazione

Servizi domiciliari

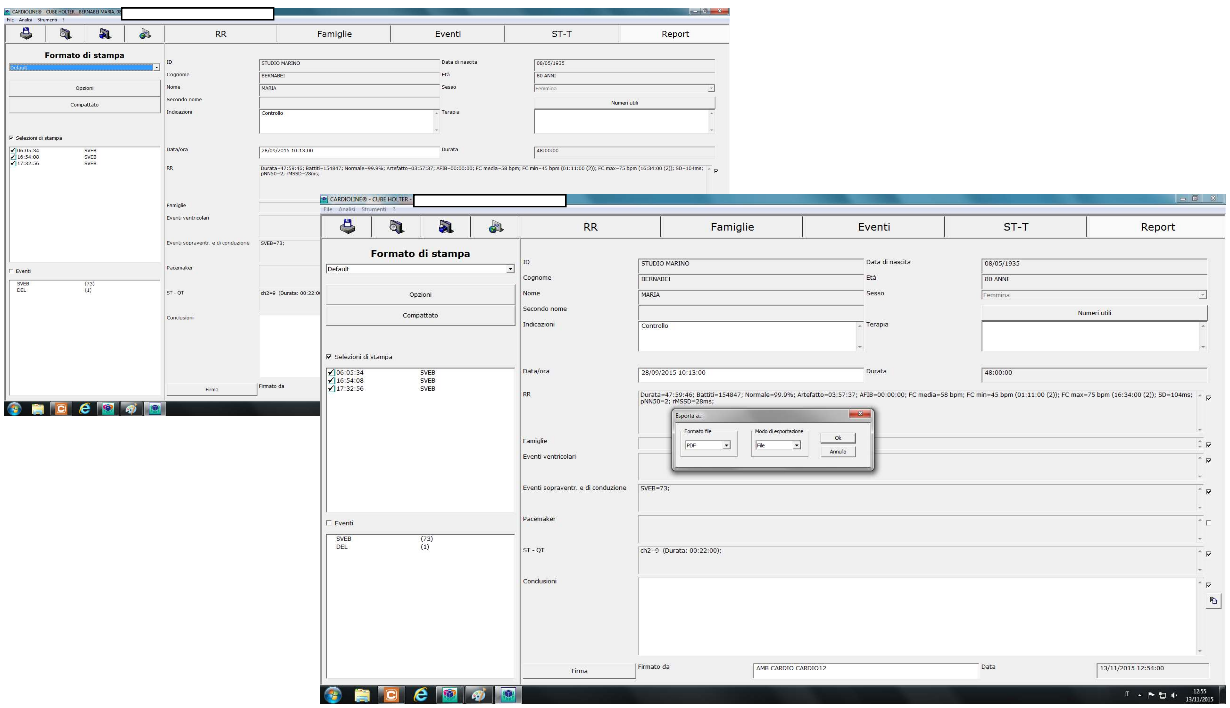
PS

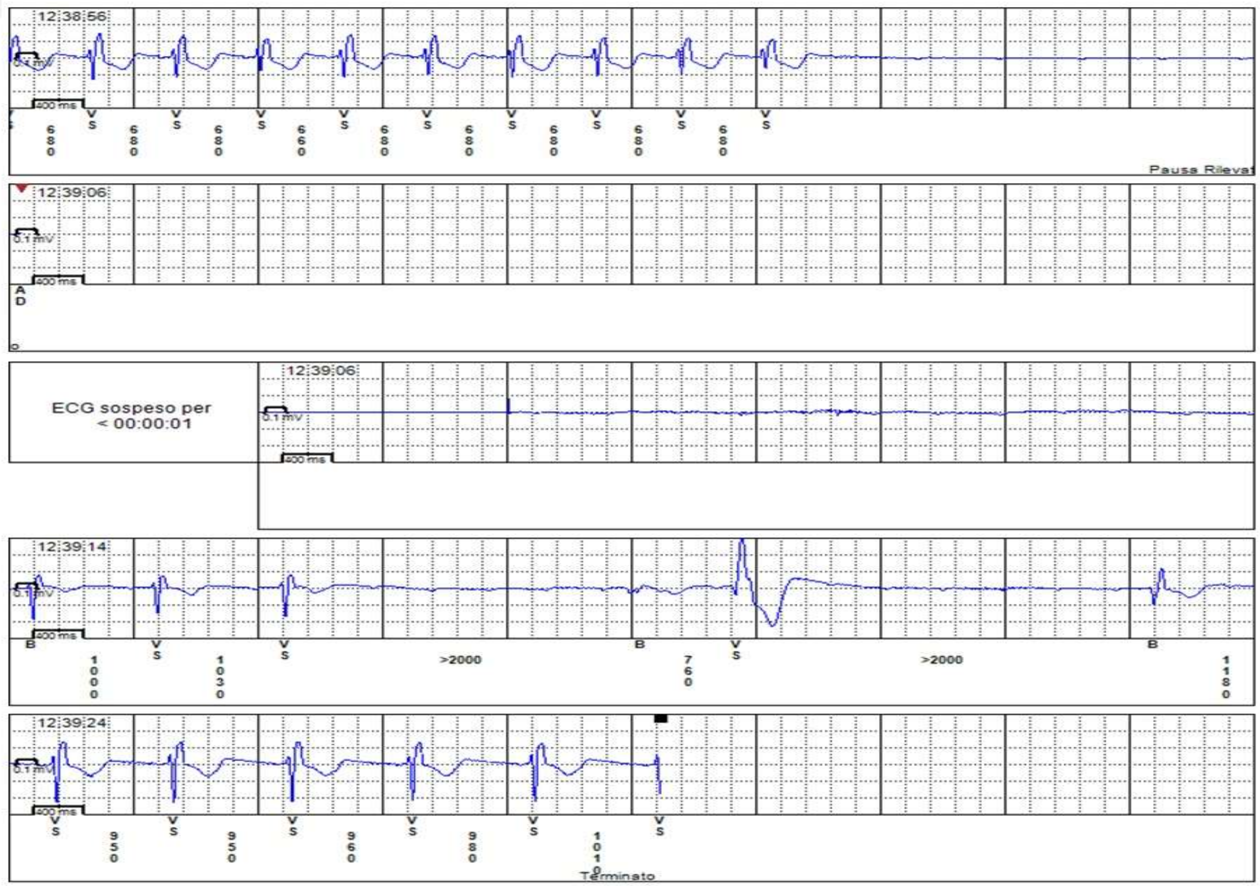


Team: 14 cardiologi, 7 tecnici, 2 infermieri

ONLINE ECG ANALYSIS

REMOTE HOLTER ECG

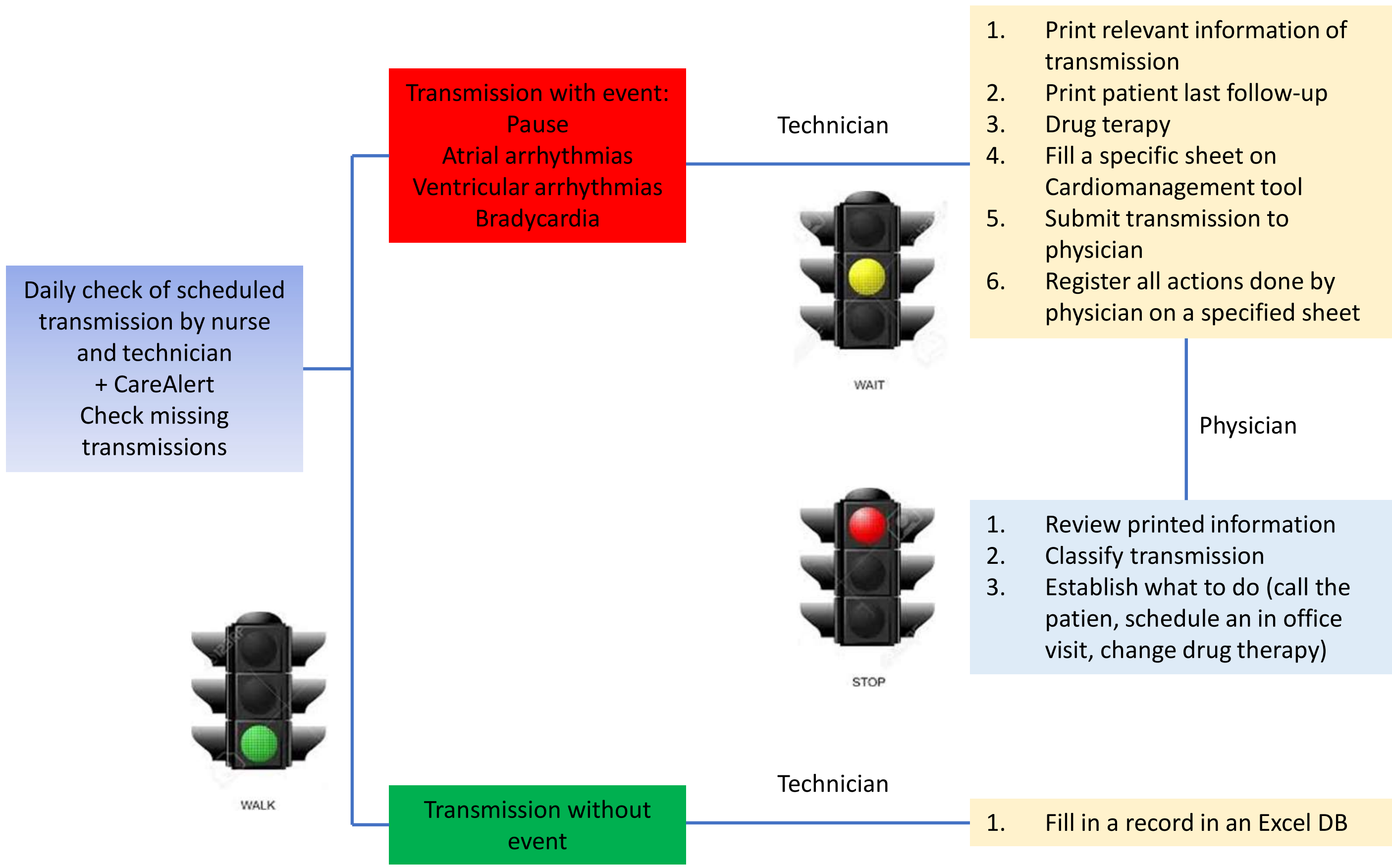



12:38:56
Pausa Rilevat
12:39:06
ECG sospeso per
< 00:00:01
12:39:06
12:39:14
>2000
>2000
12:39:24
Terminato

ORGANIZATION

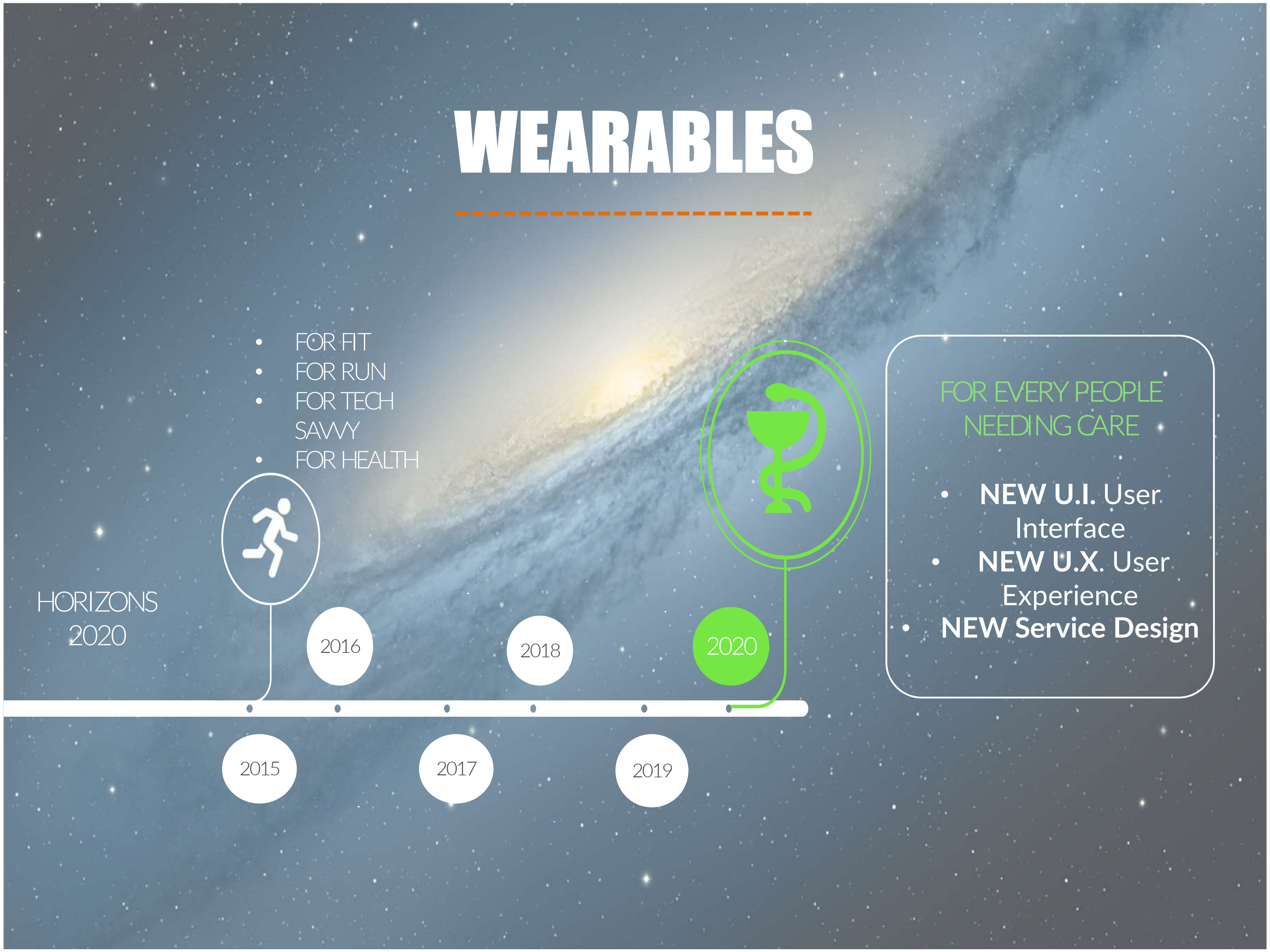
DUTIES
OF THE TECHNICIANS AND DOCTOR

REVEAL MANAGEMENT FLOW CHART




Make it easier Data Exchange
HearthTrust
Patient
SMART
SERVICE
Hospital
HEARTH TRUST
SpO2
97%
PR
79bpm
PI


Science
Translational
Medicine
28 FEBRUARY 2018
AAAS


WEARABLES
FOR FIT
FOR RUN
FOR TECH SAVVY
FOR HEALTH
HORIZONS 2020
2015
2016
2017
2018
2019
2020
FOR EVERY PEOPLE NEEDING CARE
NEW U.I. User Interface
NEW U.X. User Experience
NEW Service Design

European Heart Journal Supplements (2020) **22** (Supplement P), P8–P12
The Heart of the Matter
doi:10.1093/eurheartj/suaa170

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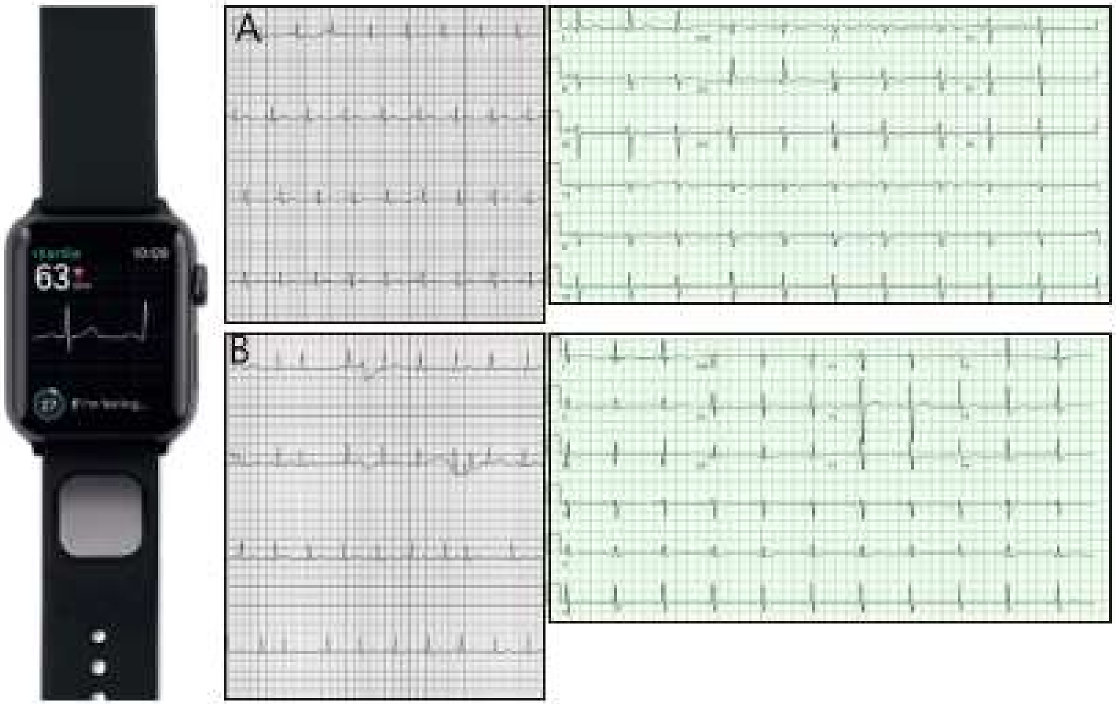
Trends beyond the new normal: from remote monitoring to digital connectivity

Leonardo Calò[1]*, Ermenegildo de Ruvo[1], Anna Maria Martino[1], Günther Prenner[2], Martin Manninger[2], and Daniel Scherr[2]


63
A
B


9:41
Edit
Medical ID
Derek Parker
April 1, 1976 (42 years old)
Medical Conditions
Hypertension
Medical Notes
In case of emergency, please call
Emily Parker.
Allergies & Reactions
Peanuts
Medications
Lisinopril (10mg by mouth once a day)
Blood Type
AB+
Weight
180 lb
Height
6'
Medical ID

Heart
Favorites
Heart
Favorites
Heart
Favorites
Heart
Favorites

Diagnostic accuracy of artificial intelligence-aided devices in identifying atrial fibrillation

Study	Device and AI algorithm	Signal analysed	AF detection
The iREAD Study William *et al.*[17]	Algorithm using smartphone (Kardia Mobile Cardiac Monitor) and handheld cardiac rhythm recorder vs. physician-interpreted ECG	ECG	96.6% sensitivity and 94.1% specificity for AF detection
HUAWEI Heart Study Guo *et al.*[18]	Wristband/wristwatch-based irregular pulse notification algorithm	PPG	Positive predictive value of PPG signals being 91.6% (95% CI 91.5–91.8%)
Apple Heart Study Perez *et al.*[19]	Smartwatch-based irregular pulse notification algorithm vs. subsequent monitoring with ECG patch	Initial PPG followed by simultaneous PPG and ECG	Smartwatch-based algorithm had a positive predictive value of 0.84 (95% CI 0.76–0.92) for observing AF during the simultaneous monitoring period
Chen *et al.*[20]	Smart wristband device enabled by AF-identifying AI algorithm vs. wristband ECG reviewed by physicians	PPG and ECG	Sensitivity, specificity, and accuracy were 88.00%, 96.41%, and 93.27%, respectively, for PPG and 87.33%, 99.20%, and 94.76% for ECG
Wasserlauf *et al.*[21]	Apple Watch with KardiaBand (enabled by convoluted neural network algorithm) vs. insertable cardiac monitor	ECG	97.5% and 97.7% for episode sensitivity and duration sensitivity, respectively
WATCH AF trial Dörr *et al.*[22]	Smartwatch-based algorithm vs. cardiologists' diagnosis by electrocardiography	PPG	Sensitivity of 93.7% (95% CI 89.8–96.4%), specificity of 98.2% (95% CI 95.8–99.4%), and 96.1% accuracy (95% CI 94.0–97.5%)

AF, atrial fibrillation; AI, artificial intelligence; CI, confidence interval; ECG, electrocardiogram; PPG, photo plethysmography.

Data di nascita: 16 set 1952 (Età: 68) Data di registrazione: 14 set 2021 - 21:15

Fibrillazione atriale — ❤ **70 BPM in media**

L'ECG mostra segni di fibrillazione atriale.

Se non ti aspettavi questo risultato, rivolgiti a un medico.

25 mm/s, 10 mm/mV, Elettrodo I, 512 Hz, iOS 14.8, watchOS 7.3, Watch6,1, Versione algoritmo 2 - L'andamento della forma d'onda è simile a quello di un ECG di tipo "Derivazione I". Per ulteriori informazioni, consulta le istruzioni d'uso.

Data di nascita: 16 set 1952 (Età: 68)

Data di registrazione: 15 set 2021 - 03:52

Fibrillazione atriale — ♥ 86 BPM in media

L'ECG mostra segni di fibrillazione atriale.

Se non ti aspettavi questo risultato, rivolgiti a un medico.

25 mm/s, 10 mm/mV, Elettrodo I, 512 Hz, iOS 14.8, watchOS 7.3, Watch6,1, Versione algoritmo 2 - L'andamento della forma d'onda è simile a quello di un ECG di tipo "Derivazione I". Per ulteriori informazioni, consulta le istruzioni d'uso.

European Heart Journal - Digital Health (2022) **3**, 311–322
https://doi.org/10.1093/ehjdh/ztac025

REVIEW

Applications of artificial intelligence and machine learning in heart failure

Tauben Averbuch [1], Kristen Sullivan[1], Andrew Sauer[2], Mamas A Mamas[3], Adriaan A. Voors[4], Chris P. Gale [5], Marco Metra[6], Neal Ravindra[7], and Harriette G.C. Van Spall [1,8,9,*]

[1]Department of Medicine, McMaster University, Hamilton, Ontario, Canada; [2]Department of Cardiology, University of Kansas Health System, Kansas City, KS, USA; [3]Keele Cardiovascular research group, Keele University, Stoke on Trent, Staffordshire; [4]University of Groningen, Groningen, The Netherlands; [5]Department of Cardiology, University of Leeds, Leeds, West Yorkshire; [6]Azienda Socio Sanitaria Territoriale Spedali Civili and University of Brescia, Brescia, Italy; [7]Department of Computer Science, Yale University, New Haven, CT, USA; [8]Population Health Research Institute, Hamilton, Ontario, Canada; and [9]Department of Health Research Methods, Evidence, and Impact, McMaster University, Hamilton, Ontario, Canada

Received 25 January 2022; revised 15 April 2022; online publish-ahead-of-print 13 May 2022

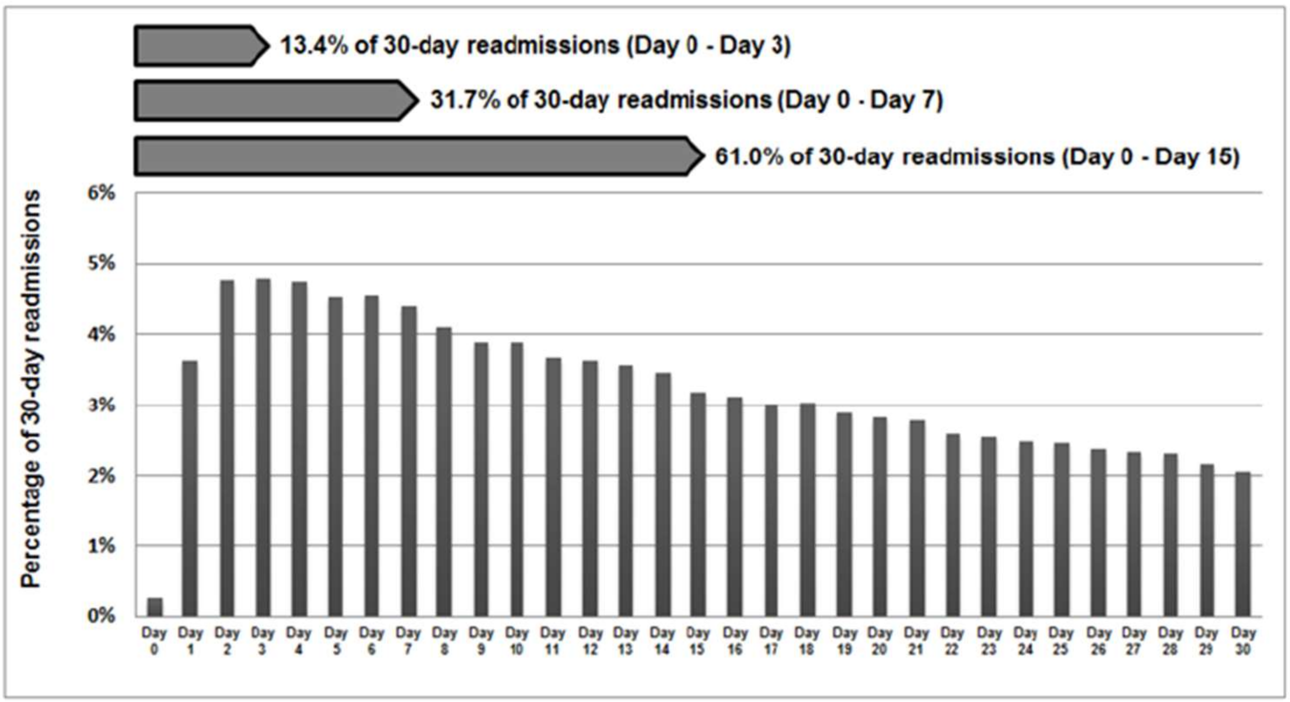
NUMBER OF ADMISSIONS IN EAD FOR ACUTE HF

N acces.	N paz	%
1	449	65,2
2	145	21,0
3	54	7,83
4	23	3,33
5	8	1,16
6	4	0,58
7	3	0,44
8	1	0,15
10	1	0,15
30	1	0,15
totale	**689**	**100**

PERCENTAGE OF 30-DAY READMISSIONS BY DAY (0–30) FOLLOWING HOSPITALIZATION FOR HEART FAILURE

30-day readmissions

24.8% readmitted



JAMA. 2013 January 23; 309(4): 355–363.

Gestione a distanza del paziente con scompenso cardiaco

European Heart Journal Supplements (2023) 25 (Supplement C), C326-C330
The Heart of the Matter
https://doi.org/10.1093/eurheartjsupp/suad029

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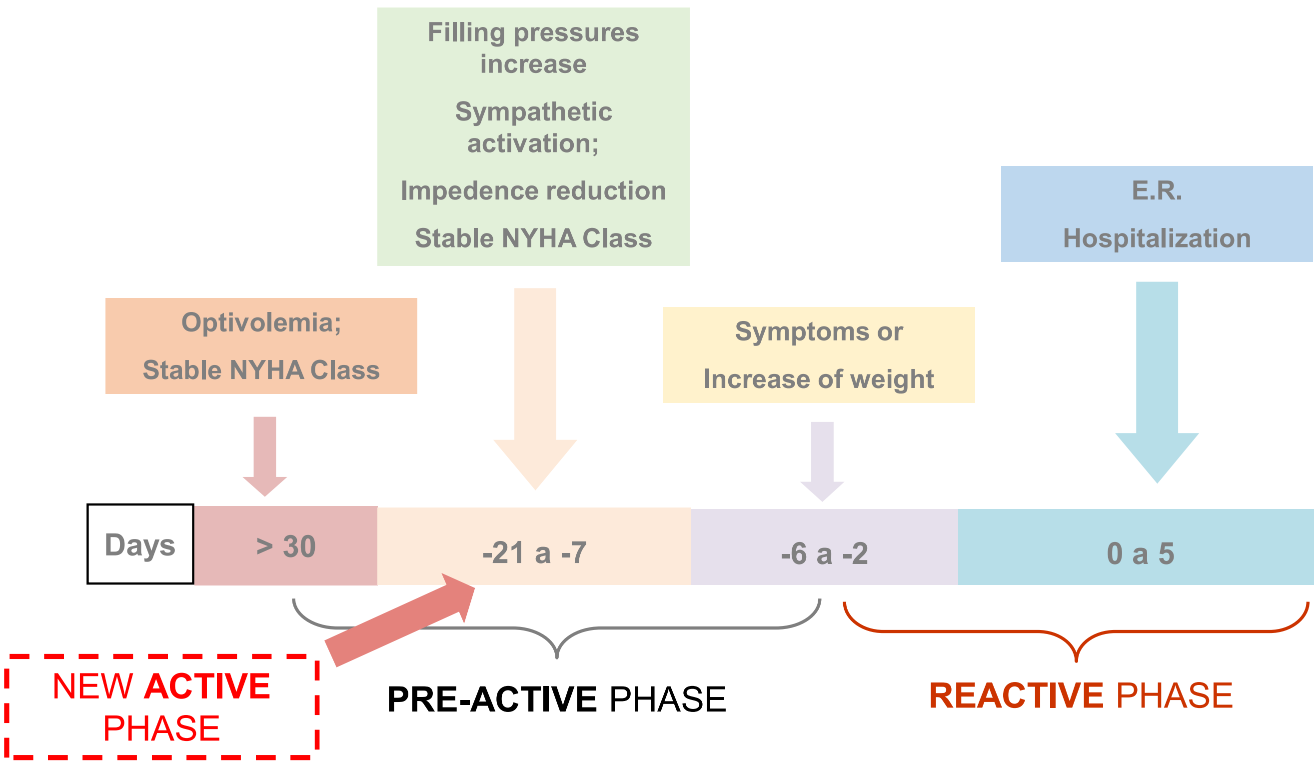
Heart failure and telemedicine: where are we and where are we going? Opportunities and critical issues

Leonardo Calò*, Annamaria Martino†, Michela Bollettino†, Ludovica Scialla, Francesco Cicogna, Claudia Tota, Beatrice Ponziani, Giada Oliviero, Marco Panuccio, Alessandro Fagagnini, Federica Toto, Francesca Fanisio, and Ermenegildo De Ruvo

Division of Cardiology, Policlinic Casilino, Via Casilina 1049, Rome 00139, Italy

*The goal of telemedicine is to **change the intervention strategy** from a **'reactive' type**, in which therapy is optimized in response to the worsening of symptoms, to a **'pro-active'** type, in which therapeutic changes are undertaken based on changes in the monitored parameters during the sub-clinical phase*

HF MANAGEMENT



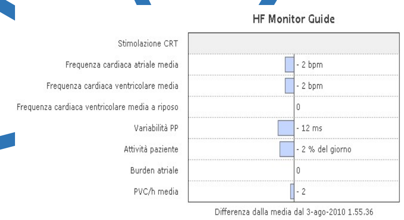
LONGITUDINAL INDICATORS

Atrial and ventricular arrhythmias

SDANN

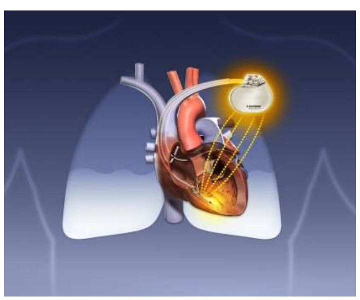
Mean heart rate / 24 h

Mean heart rate at rest



% CRT

Activity / 24h



Thoracic Fluid
(intrathoracic impedance)

Hemodynamics
(intracardiac impedance)

BP/WEIGHT

LIGHTHOUSE APPLICATION

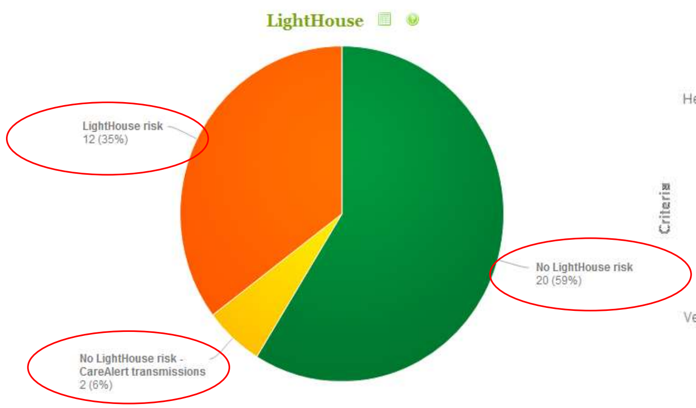
#	Device serial number	Transmission date/Time	CareAlert transmission	LightHouse risk	Risk score (0-1)	AT/AF duration evidence	Ventricular Rate evidence	OptiVol evidence	Heart Rate Veriability evidence	Night Heart Rate evidence	V. Pacing Perc. evidence
1	PZC605348S	05-11-2013 03:35	No	Yes	1	Yes	Yes	No	No	Yes	Yes
2	PZF600728S	04-11-2013 01:24	No	Yes	0.73	No	No	No	No	Yes	Yes
3	PZF605272S	04-11-2013 02:25	No	Yes	1	No	No	Yes	No	No	Yes
4	PZF601271S	04-11-2013 04:38	No	Yes	0.99	No	No	No	Yes	No	Yes
5	PZF602213S	04-11-2013 02:27	No	Yes	1	No	No	Yes	No	No	Yes
6	PZF601970S	04-11-2013 02:26	No	Yes	0.73	No	No	No	No	Yes	Yes
7	PSE600223S	15-10-2013 17:00	Yes	Yes	0.93	No	No	No	Yes	No	No
8	PZS603688S	04-11-2013 04:38	No	Yes	1	No	No	No	No	No	Yes
9	PZG600118S	18-10-2013 11:15	Yes	Yes	1	No	No	Yes	No	No	Yes
10	PZK623740S	12-10-2013 20:55	No	Yes	1	Yes	No	No	No	No	Yes

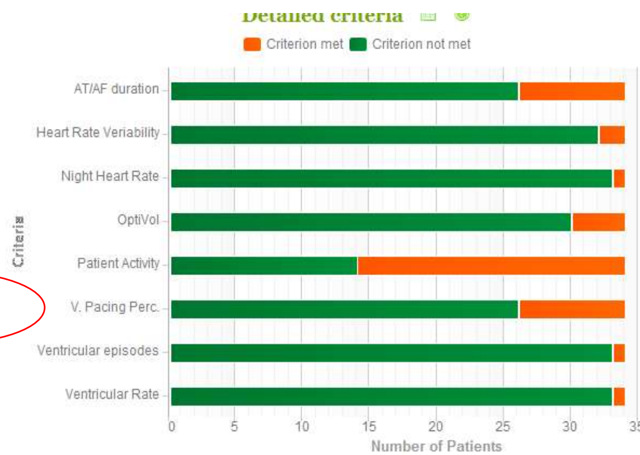
FAST

SIMPLE

COMPLIANCE

LIGHTHOUSE APP





ESC European Society of Cardiology
Europace (2021) **00**, 1–11
doi:10.1093/europace/euab170

CLINICAL RESEARCH

Combining Home Monitoring temporal trends from implanted defibrillators and baseline patient risk profile to predict heart failure hospitalizations: results from the SELENE HF study

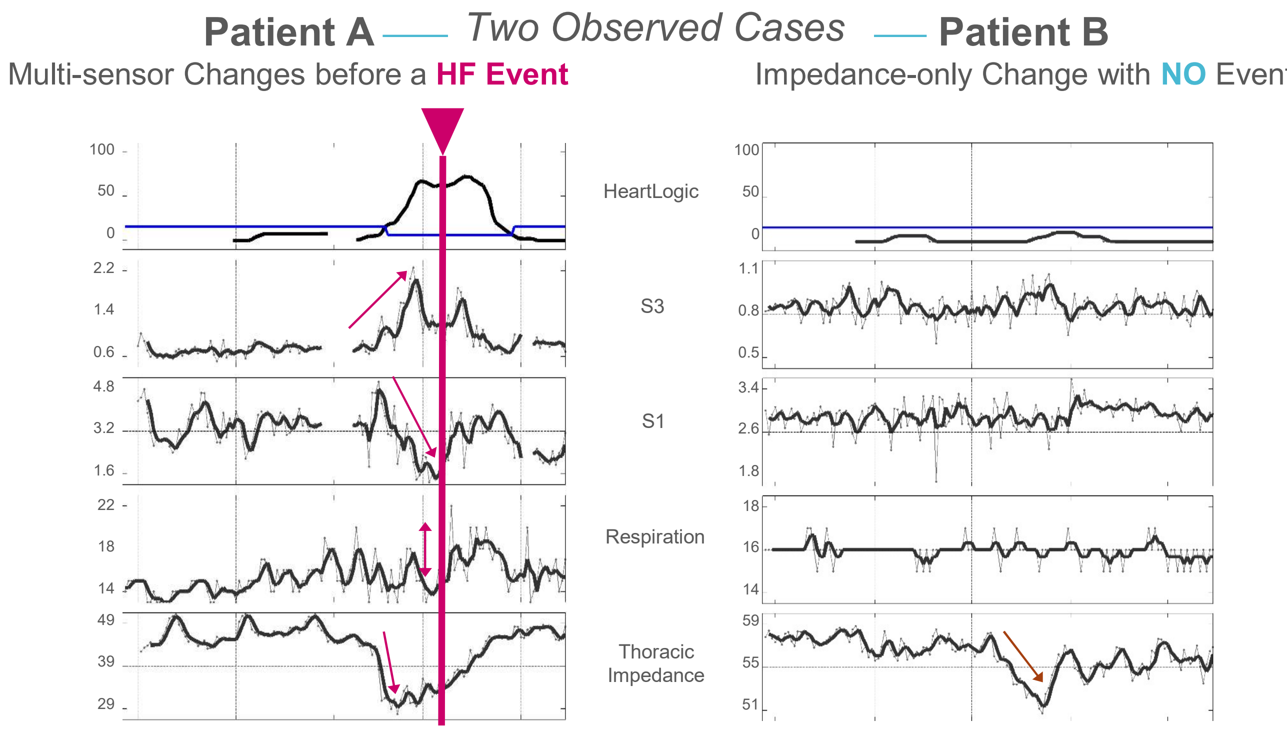
Antonio D'Onofrio[1]*, Francesco Solimene[2], Leonardo Calò[3], Valeria Calvi[4], Miguel Viscusi[5], Donato Melissano[6], Vitantonio Russo[7], Antonio Rapacciuolo[8], Andrea Campana[9], Fabrizio Caravati[10], Paolo Bonfanti[11], Gabriele Zanotto[12], Edoardo Gronda[13], Antonello Vado[14], Vittorio Calzolari[15], Giovanni Luca Botto[11], Massimo Zecchin[16], Luca Bontempi[17], Daniele Giacopelli[18], Alessio Gargaro[18], and Luigi Padeletti[19]

Aims We developed and validated an algorithm for prediction of heart failure (HF) hospitalizations using remote monitoring (RM) data transmitted by implanted defibrillators.

Methods and results The SELENE HF study enrolled 918 patients (median age 69 years, 81% men, median ejection fraction 30%) with cardiac resynchronization therapy (44%), dual-chamber (38%), or single-chamber defibrillators with atrial diagnostics (18%). To develop a predictive algorithm, temporal trends of diurnal and nocturnal heart rates, ventricular extrasystoles, atrial tachyarrhythmia burden, heart rate variability, physical activity, and thoracic impedance obtained by daily automatic RM were combined with a baseline risk-stratifier (Seattle HF Model) into one index. The primary endpoint was the first post-implant adjudicated HF hospitalization. After a median follow-up of 22.5 months since enrolment, patients were randomly allocated to the algorithm derivation group ($n = 457$; 31 endpoints) or algorithm validation group ($n = 461$; 29 endpoints). In the derivation group, the index showed a C-statistics of 0.89 [95% confidence interval (CI): 0.83–0.95] with 2.73 odds ratio (CI 1.98–3.78) for first HF hospitalization per unitary increase of index value ($P < 0.001$). In the validation group, sensitivity of predicting primary endpoint was 65.5% (CI 45.7–82.1%), median alerting time 42 days (interquartile range 21–89), and false (or unexplained) alert rate 0.69 (CI 0.64–0.74) [or 0.63 (CI 0.58–0.68)] per patient-year. Without the baseline risk-stratifier, the sensitivity remained 65.5% and the false/unexplained alert rates increased by ≈10% to 0.76/0.71 per patient-year.

Conclusion With the developed algorithm, two-thirds of first post-implant HF hospitalizations could be predicted timely with only 0.7 false alerts per patient-year.

Benefit of Multifactorial Approach



Derivazione dell'algoritmo

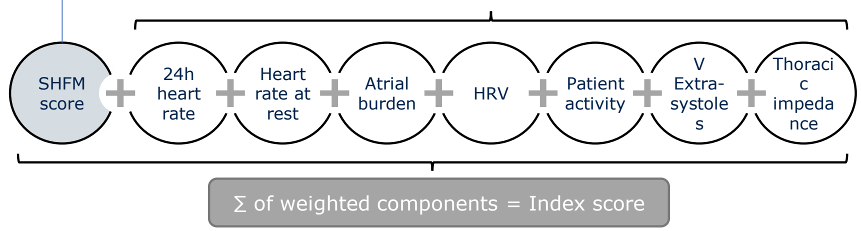
Risultati analisi cross-sectional

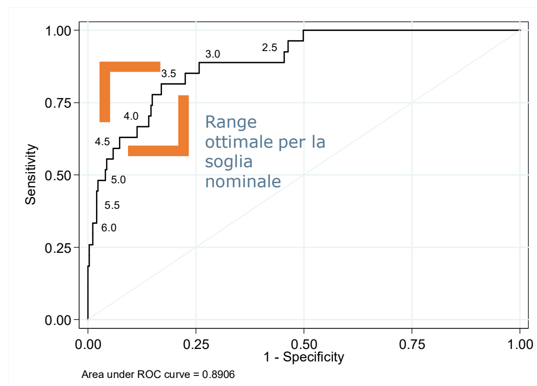
Modelli logistici univariati

Variable	Time scale	Unadjusted OR (95%CI)	P
Monotone increase in 24h HR moving average	90 days	1.04 (1.02-1.06)	<0.001
Instable nocturnal HR	45 days	1.14 (1.06-1.22)	<0.001
Monotone decrease in HRV moving average	90 days	1.16 (1.09-1.24)	<0.001
24h activity decrease	25 days	0.96 (0.94-0.99)	0.008
Atrial burden > 0% in 24h	7 days	1.24 (1.06-1.46)	0.008
Increase in moving average V extrasystoles	45 days	1.17 (1.04-1.30)	0.006
Monotone decrease in Thoracic impedance moving average	90 days	1.08 (1.04-1.12)	<0.001

Seattle Heart Failure Model
(Rischio individuale a baseline come variabile di aggiustamento)

Modello logistico multivariato



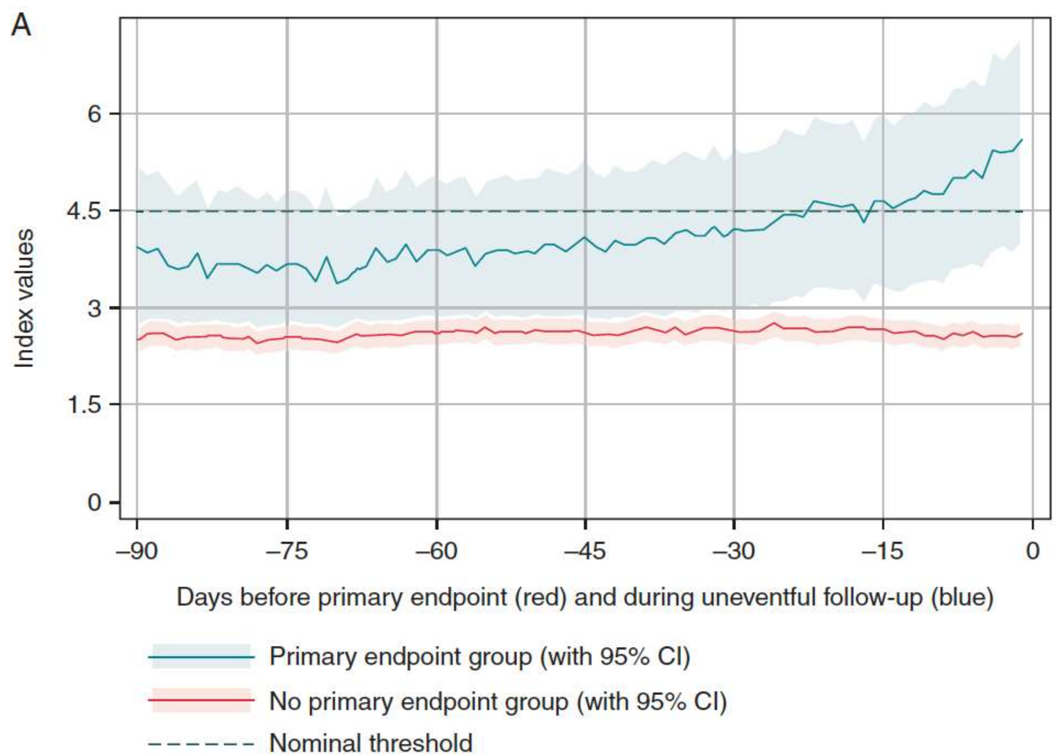


Rischio per incremento unitario del valore dell'indice
OR, 2.73 (1.98-3.78), p<0.001

Area sotto la curva ROC
0.89 (95%CI, 0.83-0.95)

Nominal Threshold (NT) ottimale
Range: 3.5 – 4.5

Temporal trends of the predicting index



The daily average values of the predicting index are plotted in patients with primary endpoint events (n = 60, blue line) vs. patients without primary endpoint events (n = 858, red line).

Circulation: Heart Failure

ORIGINAL ARTICLE

Multiparametric Implantable Cardioverter-Defibrillator Algorithm for Heart Failure Risk Stratification and Management

An Analysis in Clinical Practice

Leonardo Calò, MD; Valter Bianchi, MD; Donatella Ferraioli, MD; Luca Santini, MD; Antonio Dello Russo, MD; Cosimo Carriere, MD; Vincenzo Ezio Santobuono, MD; Chiara Andreoli, MD; Carmelo La Greca, MD; Giuseppe Arena, MD; Antonello Talarico, MD; Ennio Pisanò, MD; Amato Santoro, MD; Massimo Giammaria, MD; Matteo Ziacchi, MD; Miguel Viscusi, MD; Ermenegildo De Ruvo, MD; Monica Campari, MS; Sergio Valsecchi, PhD; Antonio D'Onofrio, MD

BACKGROUND: The HeartLogic algorithm combines multiple implantable cardioverter-defibrillator sensors to identify patients at risk of heart failure (HF) events. We sought to evaluate the risk stratification ability of this algorithm in clinical practice. We also analyzed the alert management strategies adopted in the study group and their association with the occurrence of HF events.

METHODS: The HeartLogic feature was activated in 366 implantable cardioverter-defibrillator and cardiac resynchronization therapy implantable cardioverter-defibrillator patients at 22 centers. The median follow-up was 11 months [25th–75th percentile: 6–16]. The HeartLogic algorithm calculates a daily HF index and identifies periods IN alert state on the basis of a configurable threshold.

RESULTS: The HeartLogic index crossed the threshold value 273 times (0.76 alerts/patient-year) in 150 patients. The time IN alert state was 11% of the total observation period. Patients experienced 36 HF hospitalizations, and 8 patients died of HF during the observation period. Thirty-five events were associated with the IN alert state (0.92 events/patient-year versus 0.03 events/patient-year in the OUT of alert state). The hazard ratio in the IN/OUT of alert state comparison was (hazard ratio, 24.53 [95% CI, 8.55–70.38], P<0.001), after adjustment for baseline clinical confounders. Alerts followed by clinical actions were associated with less HF events (hazard ratio, 0.37 [95% CI, 0.14–0.99], P=0.047). No differences in event rates were observed between in-office and remote alert management.

CONCLUSIONS: This multiparametric algorithm identifies patients during periods of significantly increased risk of HF events. The rate of HF events seemed lower when clinical actions were undertaken in response to alerts. Extra in-office visits did not seem to be required to effectively manage HeartLogic alerts.

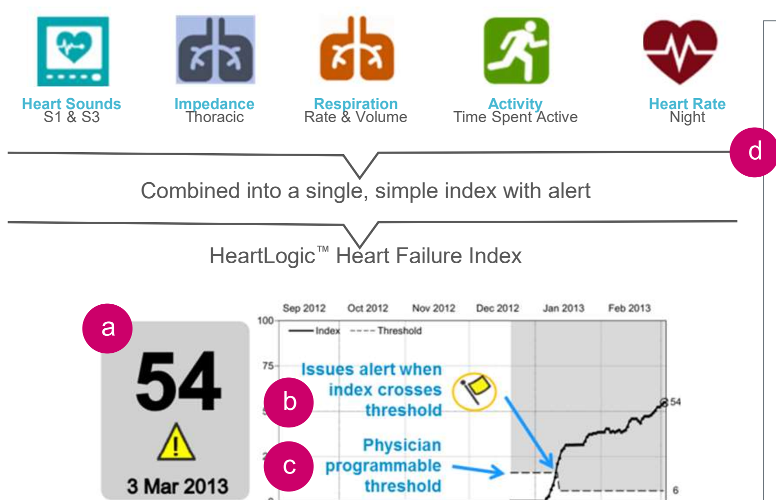
REGISTRATION: URL: https://www.clinicaltrials.gov; Unique identifier: NCT02275637.

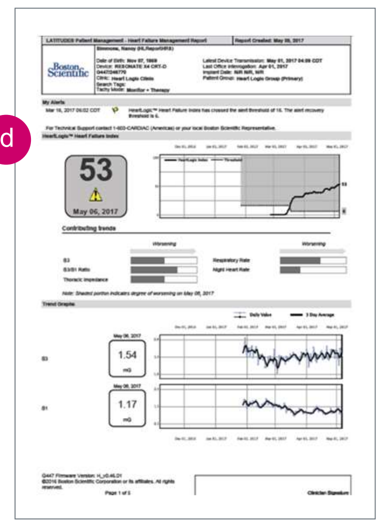
HeartLogic – Heart Failure Diagnostic

HeartLogic was proven to detect the early warning signs of worsening heart failure by combining data from **5 sensors** into a single composite index.

HeartLogic is composed by HF related sensors (heart souts, respiratory rate) and not ony rhythm sensor

Multiple Sensor Measurements





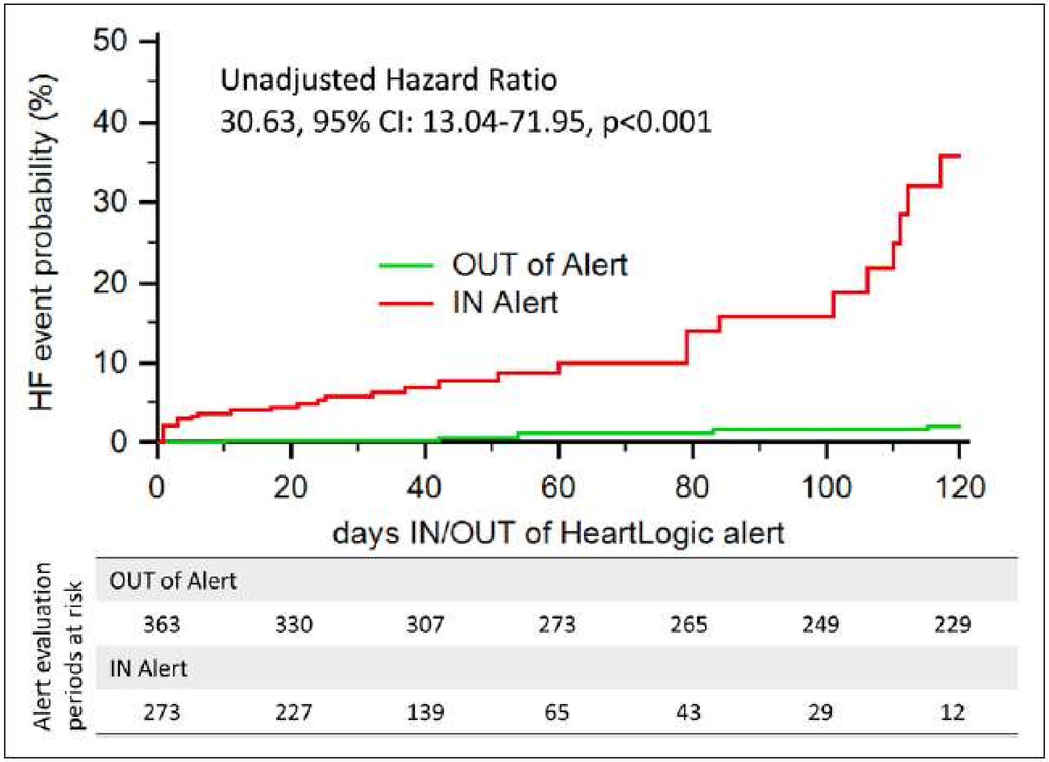
HeartLogic™ Includes:

a Composite HeartLogic™ Index trend

b Actionable HeartLogic™ Alert

c Configurable HeartLogic™ Threshold

d Heart Failure Management Report with HeartLogic™ Data



- 35 events occurred in the HeartLogic IN alert state (an event rate of 0.92/patient-year)
- 9 events occurred in the HeartLogic OUT of alert state (a rate of 0.03/patient-year)

Comparison of the event rates in the IN alert state with those in the OUT of alert state yielded a hazard ratio (HR) of 30.63 (Figure 1)

Results

The HeartLogic feature was activated in **366 ICD and CRT-D** patients at 22 centers.

During a median follow-up of 11 months, **273 HeartLogic alerts** occurred (**0.76 alerts/patient-year**) in 150 patients and **the time IN the alert state was 11%** of the total observation period.

MultiSENSE: 1.6 alerts/patient-year
Capucci et al.: 0.99 alerts/patient-year
Santini et al.: 0.93 alerts/patient-year

MultiSENSE: 17%
Capucci et al.: 12%
Santini et al.: 15%

HeartLogic Alerts and Heart Failure Events

During the observation period,

- ✓ 21 patients experienced **36 HF hospitalizations**
- ✓ **8 patients died of HF**

The rate of hospitalizations or death due to HF was 0.12/patient-year

Table 2. **Univariate Analysis of Variables Associated With a HF Event**

	Univariate analysis		
	Hazard ratio	**95% CI**	***P* value**
Male sex	0.45	0.17–1.18	0.106
Age	1.01	0.95–1.08	0.716
NYHA class	2.80	0.96–3.38	0.067
LV ejection fraction	0.99	0.94–1.04	0.613
AF history	1.75	1.20–2.57	0.004
Coronary artery disease	1.17	0.42–3.21	0.768
Diabetes	2.12	0.72–6.26	0.172
COPD	3.07	0.94–8.56	0.066
Chronic kidney disease	3.55	1.29–9.76	0.014
Hypertension	0.81	0.30–2.21	0.685
CRT device	1.42	0.46–4.35	0.544
HeartLogic Alert	30.63	13.04–71.95	<0.001

AF indicates atrial fibrillation; COPD, chronic obstructive pulmonary disease; CRT, cardiac resynchronization therapy; HF, heart failure; LV, left ventricle; and NYHA, New York Heart Association.

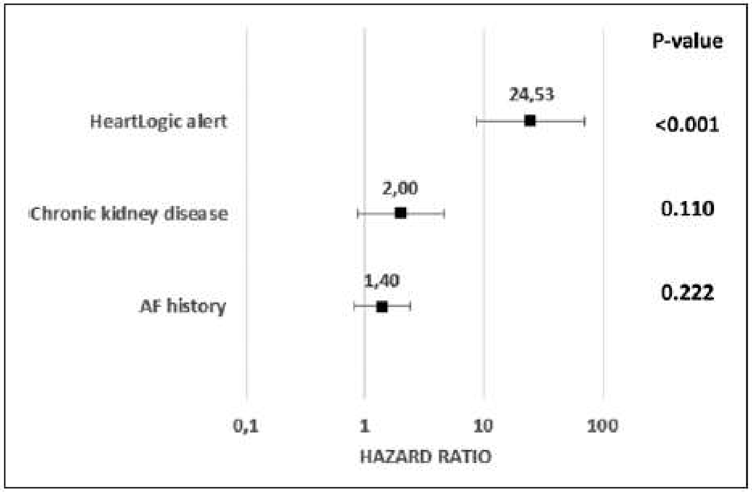
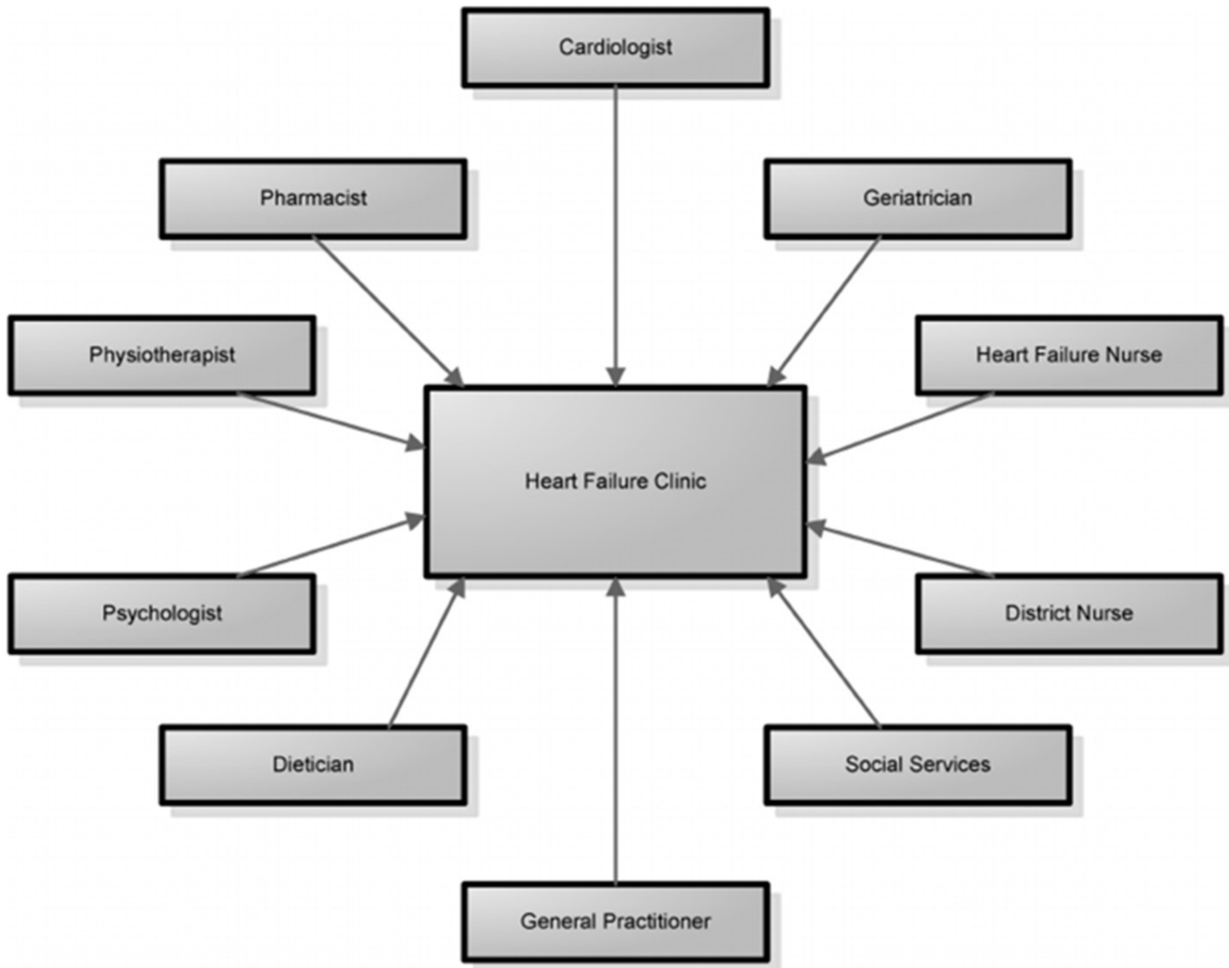
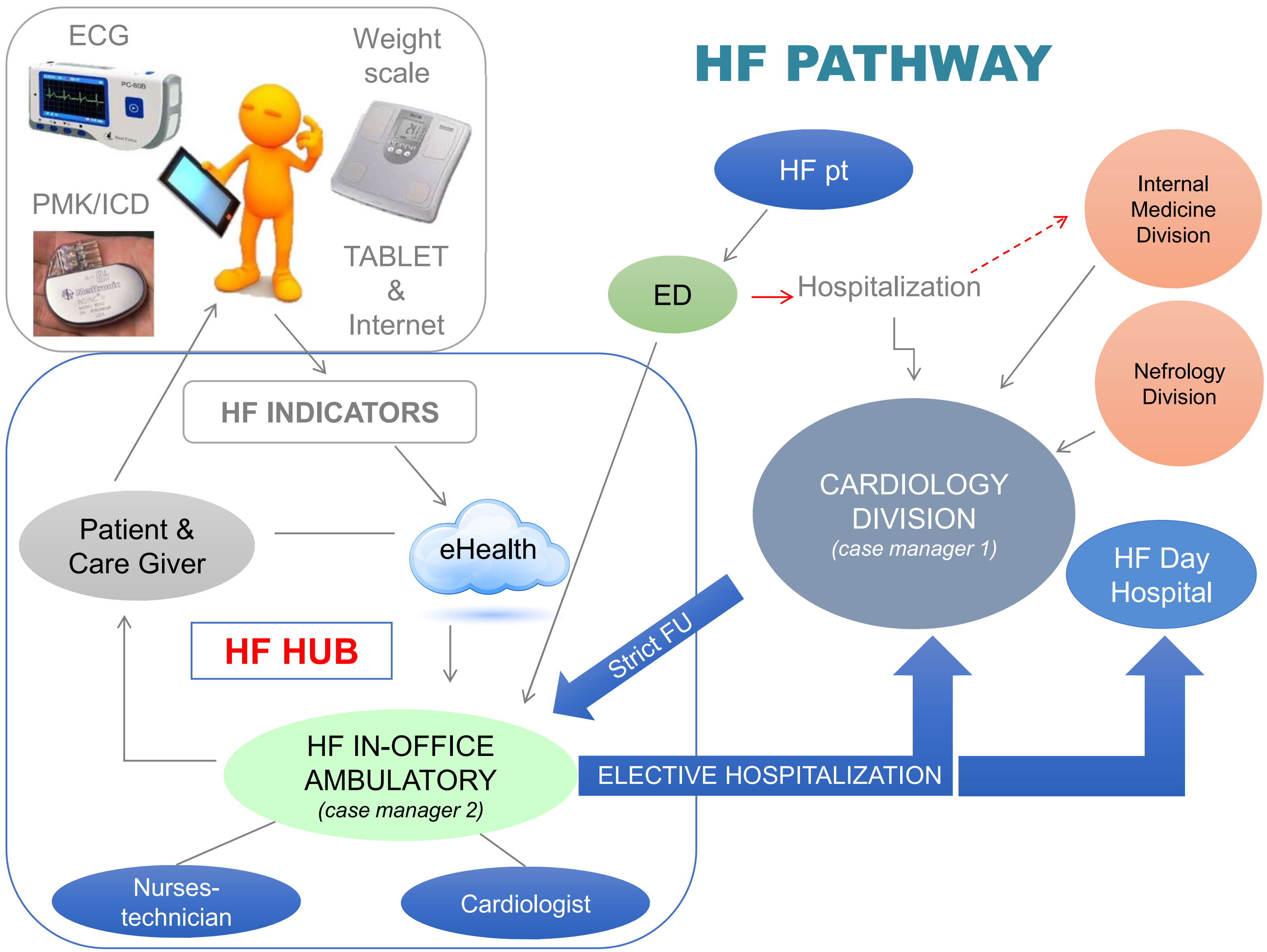


Figure 2. **Multivariate analysis.**
Patients had a 24.53-fold increased risk of an heart failure event after HeartLogic alert, after adjusting for clinical variables. AF indicates atrial fibrillation.

The results were similar (HR, 24.53 [95% CI, 8.55–70.38], *P*<0.001) when the model was adjusted for those baseline clinical variables (chronic kidney disease and history of atrial fibrillation) that had proved to be associated with the occurrence of events on univariate analysis.(Figure 3)

PROCESS CONTROL


Cardiologist
Pharmacist
Geriatrician
Physiotherapist
Heart Failure Nurse
Heart Failure Clinic
Psychologist
District Nurse
Dietician
Social Services
General Practitioner


HF PATHWAY
ECG
Weight scale
PMK/ICD
TABLET & Internet
HF INDICATORS
Patient & Care Giver
eHealth
HF HUB
HF IN-OFFICE AMBULATORY
(case manager 2)
Nurses-technician
Cardiologist
HF pt
ED
Hospitalization
Internal Medicine Division
Nefrology Division
CARDIOLOGY DIVISION
(case manager 1)
HF Day Hospital
Strict FU
ELECTIVE HOSPITALIZATION

Telemonitoraggio e scompenso cardiaco

Nuove opportunità

European Heart Journal Supplements (2023) 25 (Supplement C), C344–C348
The Heart of the Matter
https://doi.org/10.1093/eurheartjsupp/suad031

ESC
European Society
of Cardiology

The implantable cardiac monitor in heart failure patient: a possible new indication?

Francesco Cicogna[1]*, Oreste Lanza[1], Luca Monzo[1,2], Claudia Tota[1], Gennaro Cice[1], Ermenegildo De Ruvo[1], and Leonardo Calò[1]

[1]*Department of Cardiology, Policlinico Casilino, Via Casilina 1049, 1069 Rome, Italy; and* [2]*Centre d'Investigations Cliniques Plurithématique, Université de Lorraine INSERM, Nancy, France*

Why?	**When?**	**What?**
- Early detection of arrhythmias requiring treatment - To reduce cerebrovascular events and cognitive impairment - To prevent rehospitalizations - Potential reduction in treatment costs	- Clinically stable patients - After excluding indication to other types of devices	- ICM with remote monitoring system - ICM equipped with tools capable of predicting exacerbations of heart failure
Where?	**To Whom?**	**How?**
- Heart failure clinic: Monitoring informations should be handled by the heart failure clinic staff	- HFmrEF and HFpEF patients without any other devices - Individuals with no history of atrial fibrillation without indication to other types of CIED	- Tailored approach to device programming and alarm management and review

Telemonitoraggio e scompenso cardiaco

Il futuro: Information overload, artificial intelligence and machine learning?

REMOTE MANAGEMENT OF HEART FAILURE WITH PRESERVED EJECTION FRACTION: A SINGLE CENTER EXPERIENCE

INTRODUCTION

Experience of remote monitoring (RM) management of Heart failure

RESULTS

Overall 26 HFpEF patients were prospectively enrolled for remote

(absence of measurements).

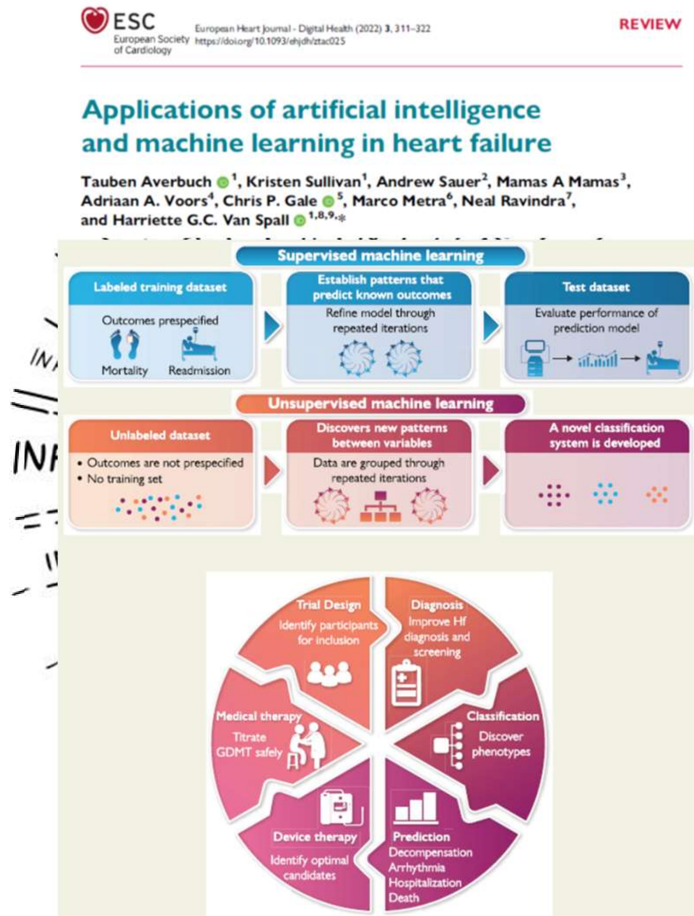
47.900 €.

8 HF HOSPITALIZATIO NS AVOIDED

OVER 20.000 € SAVED

CONCLUSIONS

The RM of HfpEF with the DPS has showed a great power in reducing HF hospitalizations. It has been considered a self-coverage and cost-effective service eligible to provide a better service at a lower cost. We observed that erroneous measurements performed by the patients, and the consequent false alarms, represented the greatest weakness point of this system, suggesting the need for adequate patients's selection and training.



ESC European Society of Cardiology

European Heart Journal - Digital Health (2022) 3, 311–322
https://doi.org/10.1093/ehjdh/ztac025

REVIEW

Applications of artificial intelligence and machine learning in heart failure

Tauben Averbuch[1], Kristen Sullivan[1], Andrew Sauer[2], Mamas A Mamas[3], Adriaan A. Voors[4], Chris P. Gale[5], Marco Metra[6], Neal Ravindra[7], and Harriette G.C. Van Spall[1,8,9,*]

Telemonitoraggio e scompenso cardiaco

Sfide aperte

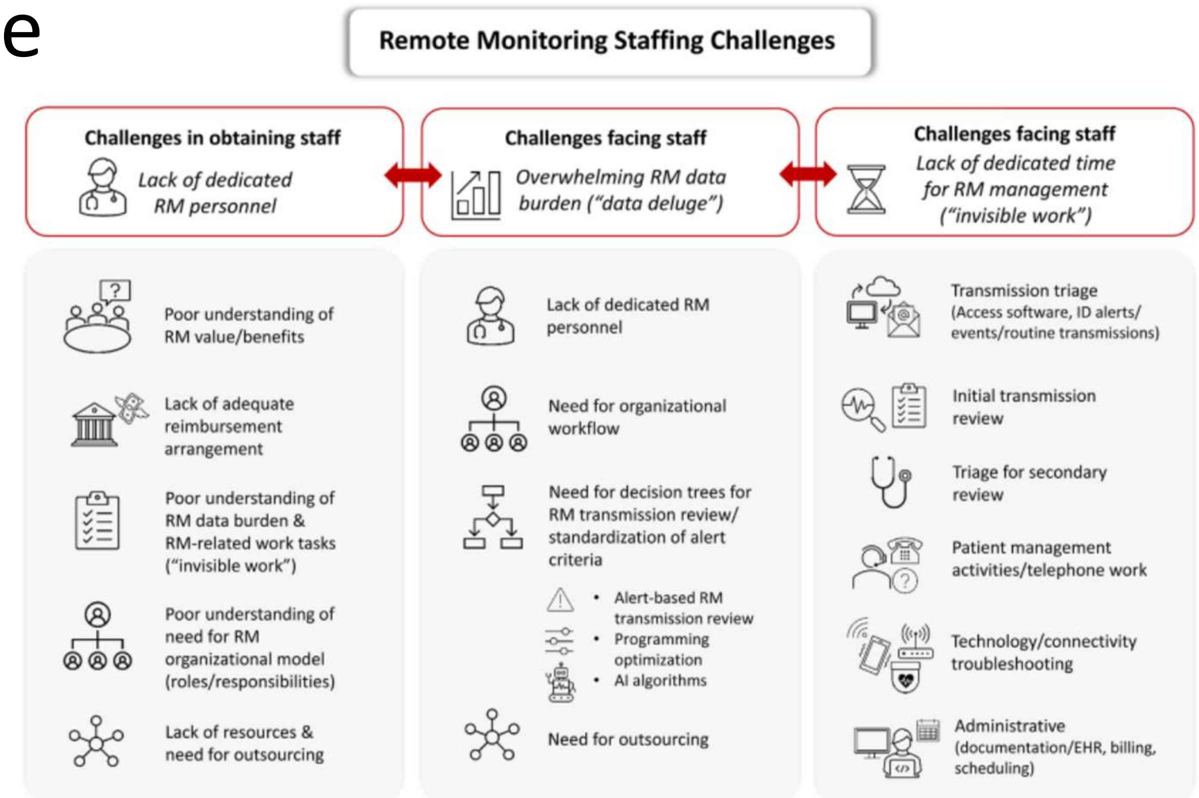
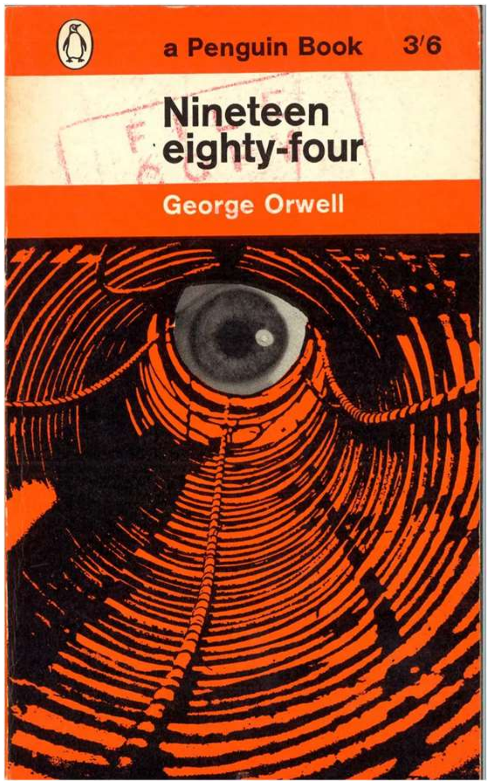


Figure 1 Staffing challenges with remote monitoring. AI = artificial intelligence; EHR = electronic health record; RM = remote monitoring.

2023 HRS/EHRA/APHRS/LAHRS expert consensus statement on practical management of the remote device clinic

Telemonitoraggio e scompenso cardiaco

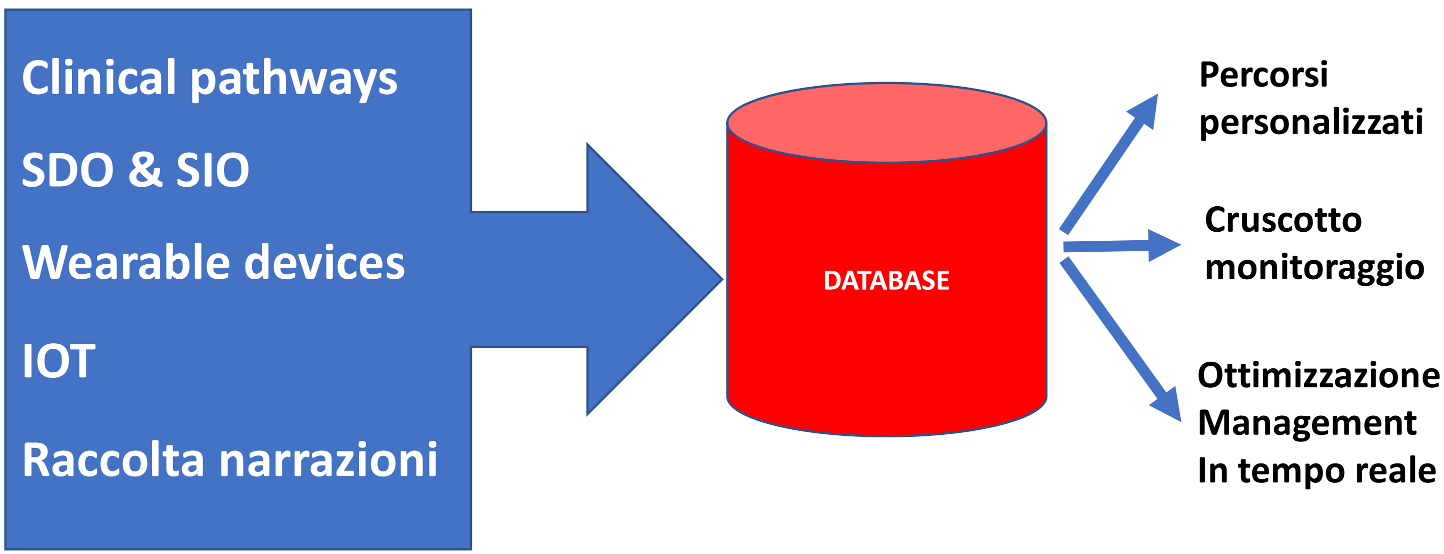
Controllo → Cura……

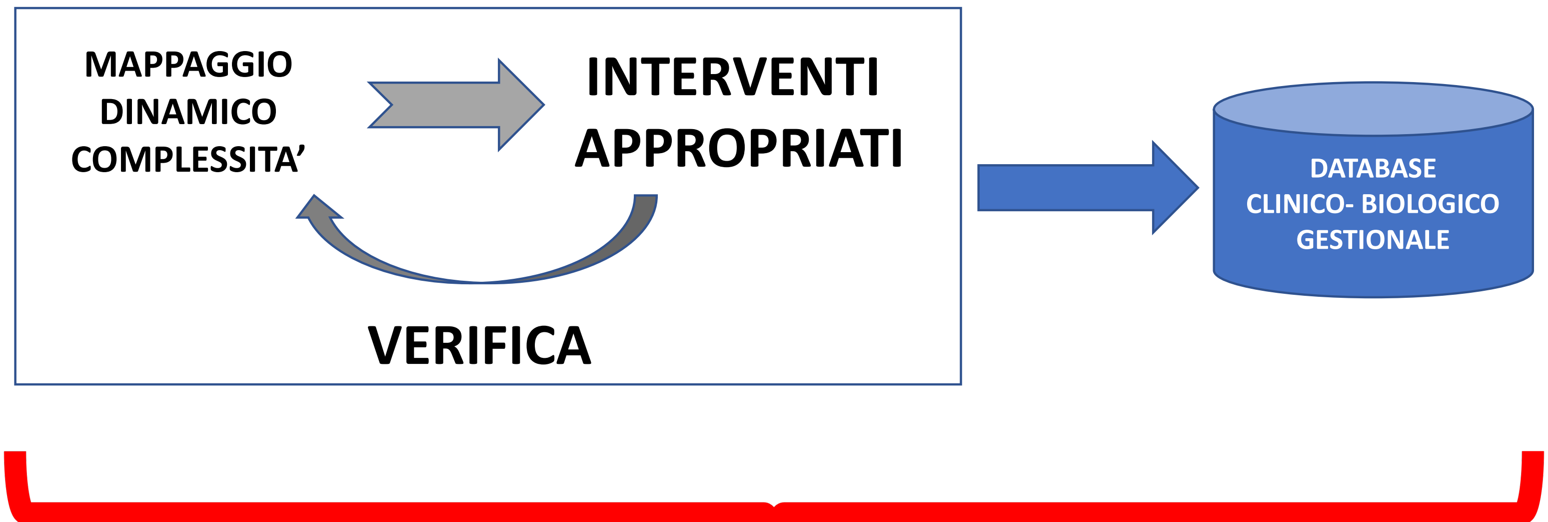


CURA

- Raccolta di informazioni (informazioni generali, storia clinica, sintomi, segni, dati)
- Integrazione ed interpretazione delle informazioni
- Elaborazione di una strategia di intervento terapeutico
- Adeguata comunicazione al soggetto in cura della situazione, delle misure che si intende mettere in atto e dei risultati attesi
- Supporto al soggetto in cura durante l'attuazione dell'intervento terapeutico
- Rivalutazione periodica del quadro

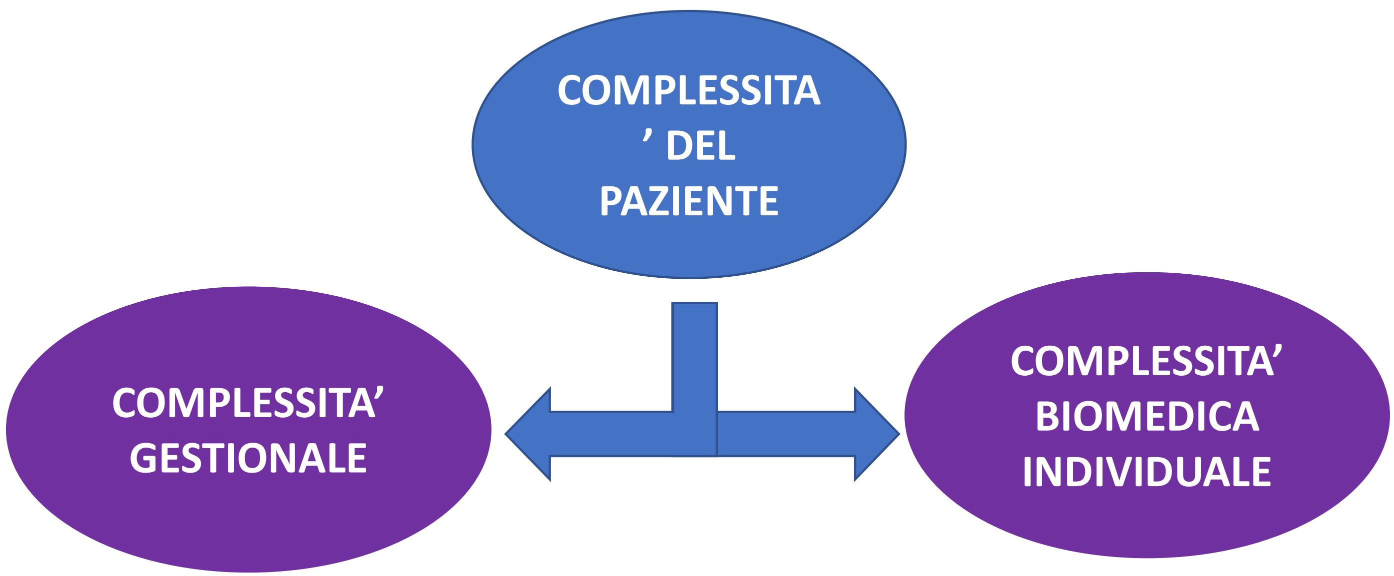
MONITORAGGIO PERCORSI E MANAGEMENT





<u>CENTRO MEDICINA PERSONALIZZATA</u>

PERSONALIZZARE SIGNIFICA RISPONDERE ALLA COMPLESSITA'



Telemonitoraggio:

Quanti medici e sanitari se ne occupano?

Tutti o quasi…..nostro malgrado!