SCOMPENSO CARDIACO 3D

SCOMPENSO E TELEMEDICINA: DOVE SIAMO E DOVE ANDIAMO. CRITICITA' ED OPPORTUNITA'

L. Calò, Roma

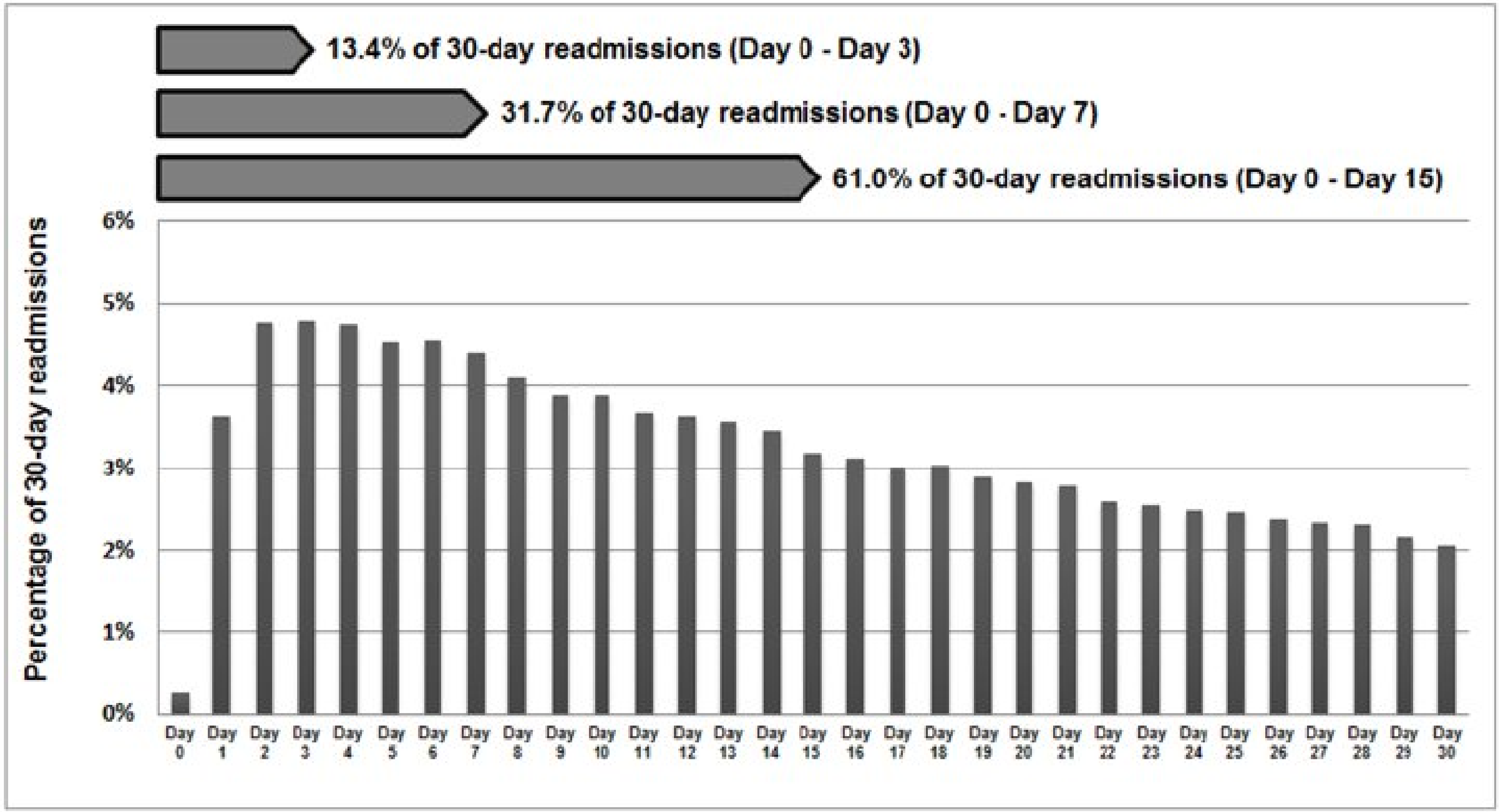
NUMBER OF ADMISSIONS IN EAD FOR ACUTE HF

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

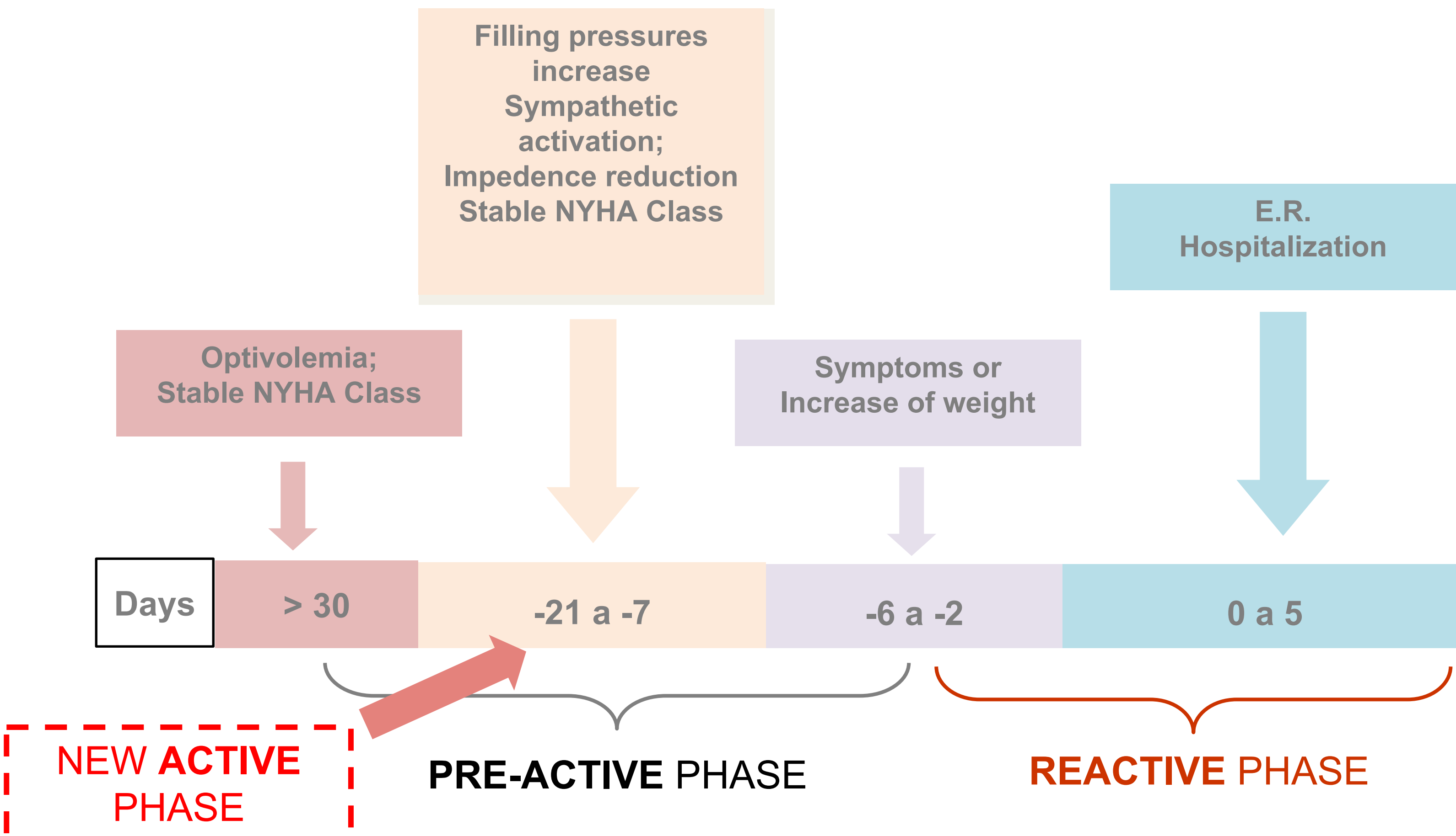
30-day readmissions

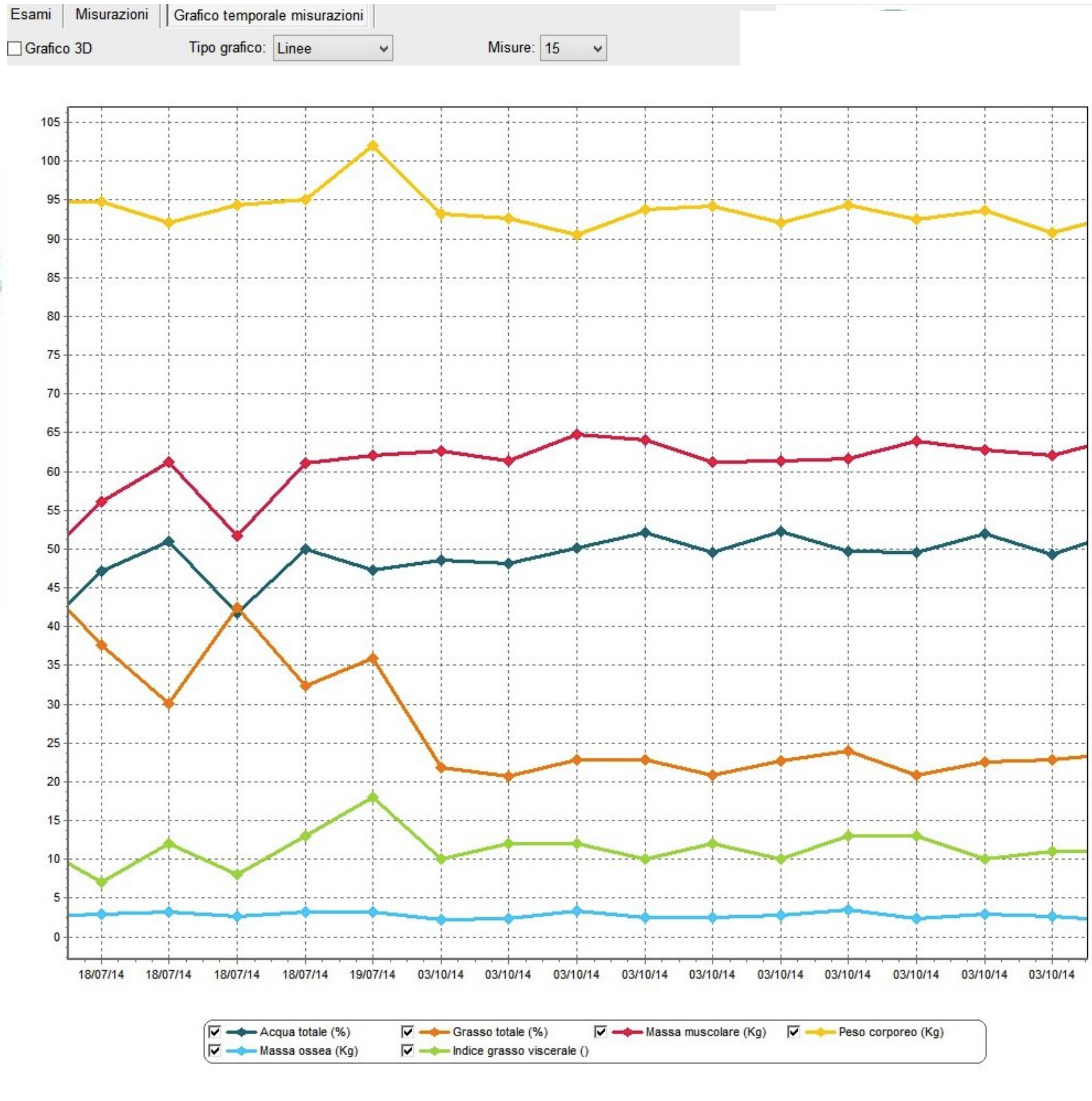
24.8% readmitted



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

HF MANAGEMENT





Esami
Misurazioni
Grafico temporale misurazioni
Grafico 3D
Tipo grafico: Linee
Misure: 15
105
100
95
90
85
80
75
70
65
60
55
50
45
40
35
30
25
20
15
10
5
0
18/07/14
18/07/14
18/07/14
18/07/14
19/07/14
03/10/14
03/10/14
03/10/14
03/10/14
03/10/14
03/10/14
03/10/14
03/10/14
03/10/14
03/10/14
Acqua totale (%)
Grasso totale (%)
Massa muscolare (Kg)
Peso corporeo (Kg)
Massa ossea (Kg)
Indice grasso viscerale ()

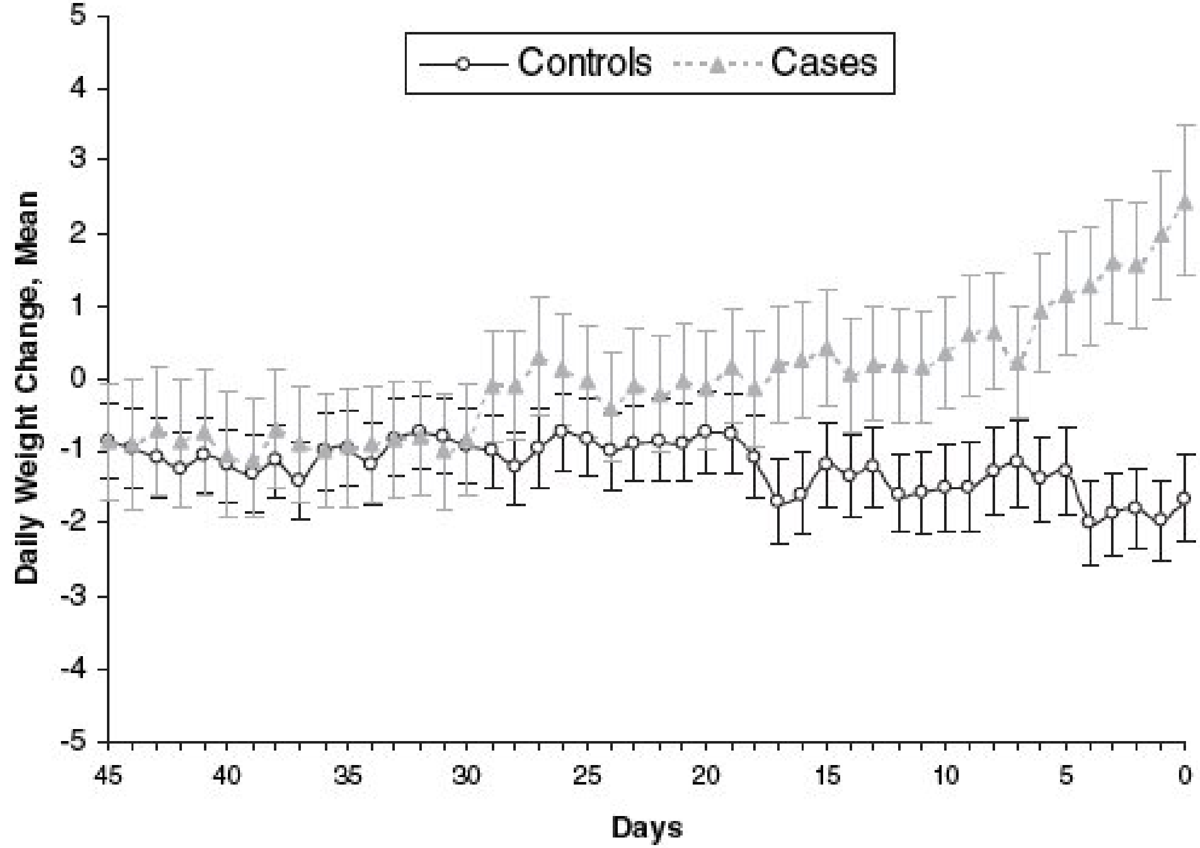
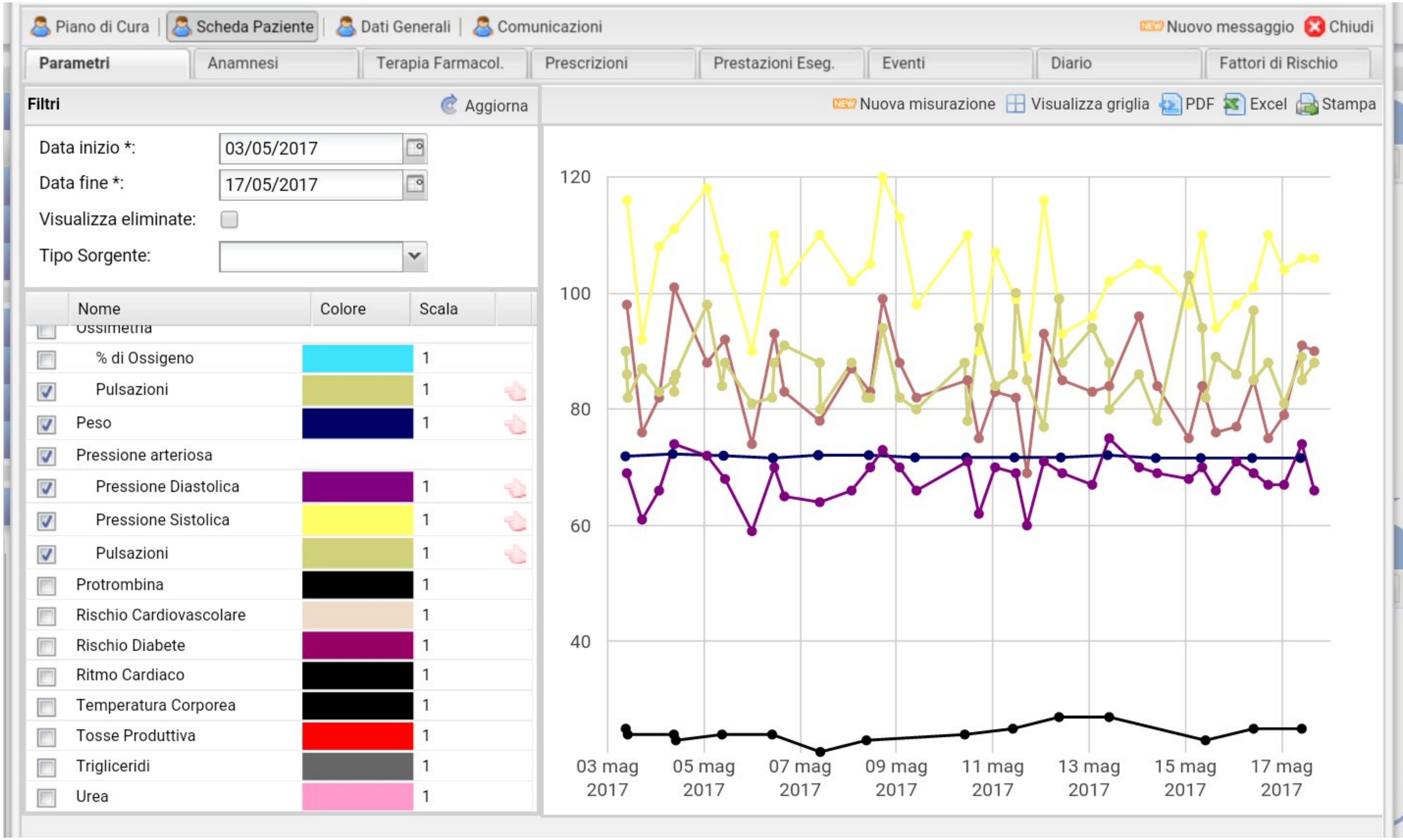


Figure 1. Daily weight change before heart failure hospitalization: cases vs controls. n=268. "Days" on the x-axis denotes days before hospital admission in case patients. The difference in daily weight changes between case and control patients within 30 days before (case) hospitalization was statistically significant ($P<0.001$) on the basis of a generalized linear model with daily weight change as the dependent variable.



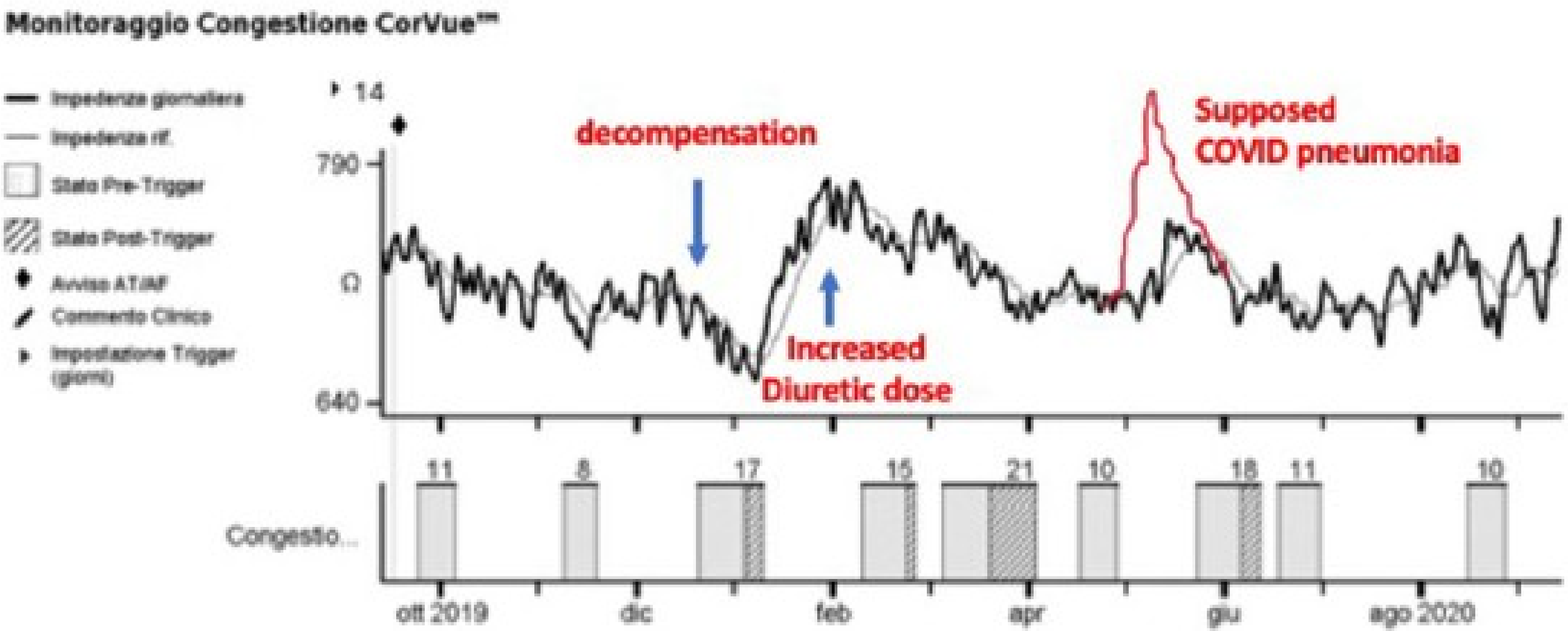
Piano di Cura
Scheda Paziente
Dati Generali
Comunicazioni
Nuovo messaggio
Chiudi
Parametri
Anamnesi
Terapia Farmacol.
Prescrizioni
Prestazioni Eseg.
Eventi
Diario
Fattori di Rischio
Filtri
Aggiorna
Data inizio *:
03/05/2017
Data fine *:
17/05/2017
Visualizza eliminate:
Tipo Sorgente:
Nome
Colore
Scala
% di Ossigeno 1
Pulsazioni 1
Peso 1
Pressione arteriosa
Pressione Diastolica 1
Pressione Sistolica 1
Pulsazioni 1
Protrombina 1
Rischio Cardiovascolare 1
Rischio Diabete 1
Ritmo Cardiaco 1
Temperatura Corporea 1
Tosse Produttiva 1
Trigliceridi 1
Urea 1
Nuova misurazione
Visualizza griglia
PDF
Excel
Stampa
120
100
80
60
40
03 mag 2017
05 mag 2017
07 mag 2017
09 mag 2017
11 mag 2017
13 mag 2017
15 mag 2017
17 mag 2017

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

ESC
European Society
of Cardiology

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

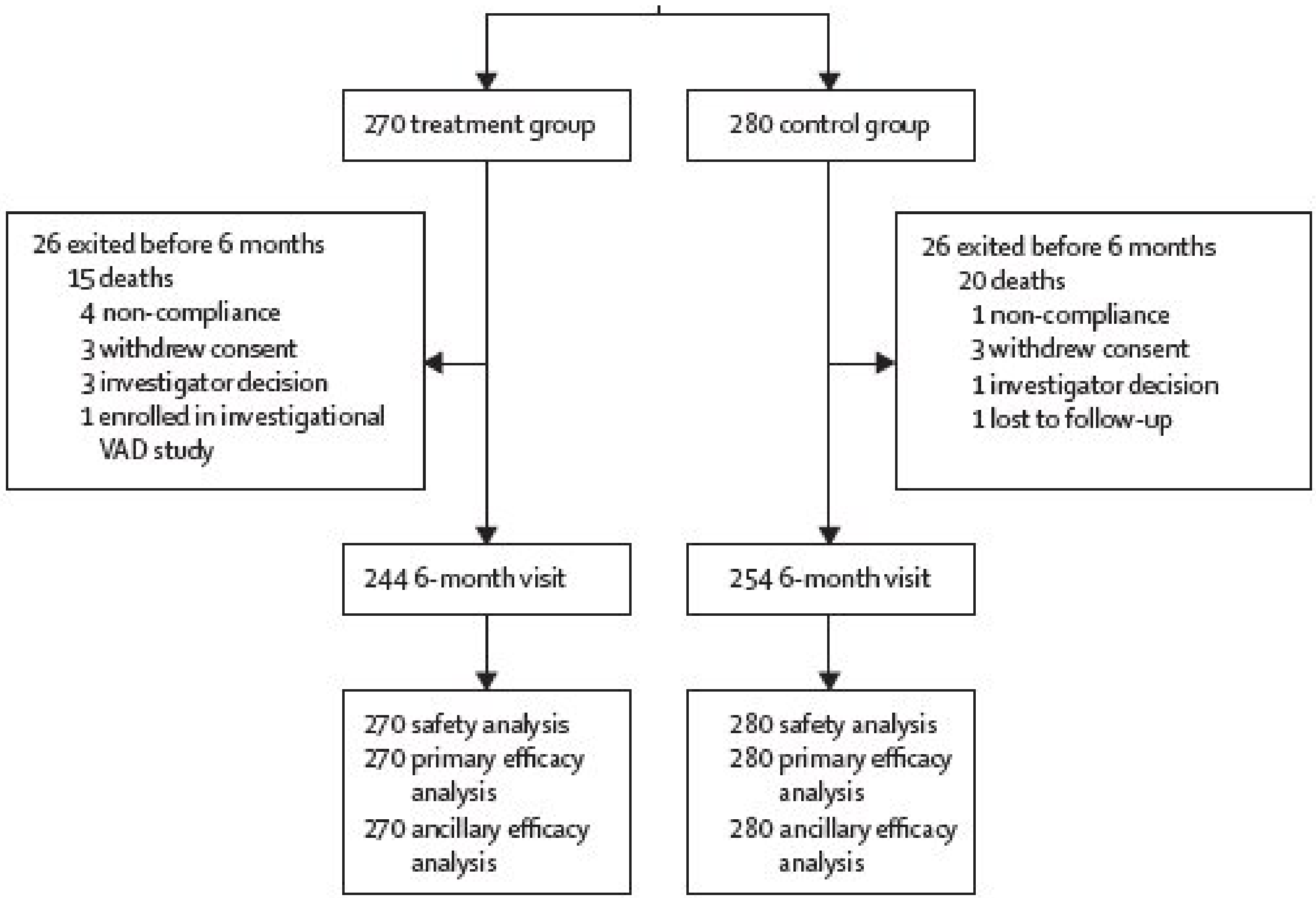
Leonardo Calò[1]*, Ermenegildo de Ruvo[1], Anna Maria Martino[1],
Günther Prenner[2], Martin Manninger[2], and Daniel Scherr[2]



Monitoraggio Congestione CorVue™
Impedenza giornaliera
Impedenza rif.
Stato Pre-Trigger
Stato Post-Trigger
Avviso AT/AF
Commento Clinico
Impostazione Trigger (giorni)
14
790
Ω
640
decompensation
Increased Diuretic dose
Supposed COVID pneumonia
11
8
17
15
21
10
18
11
10
Congestio...
ott 2019
dic
feb
apr
giu
ago 2020

Wireless pulmonary artery haemodynamic monitoring in chronic heart failure: a randomised controlled trial

*William T Abraham, Philip B Adamson, Robert C Bourge, Mark F Aaron, Maria Rosa Costanzo, Lynne W Stevenson, Warren Strickland, Suresh Neelagaru, Nirav Raval, Steven Krueger, Stanislav Weiner, David Shavelle, Bradley Jeffries, Jay S Yadav, for the CHAMPION Trial Study Group**



Lancet 2011; 377: 658–66

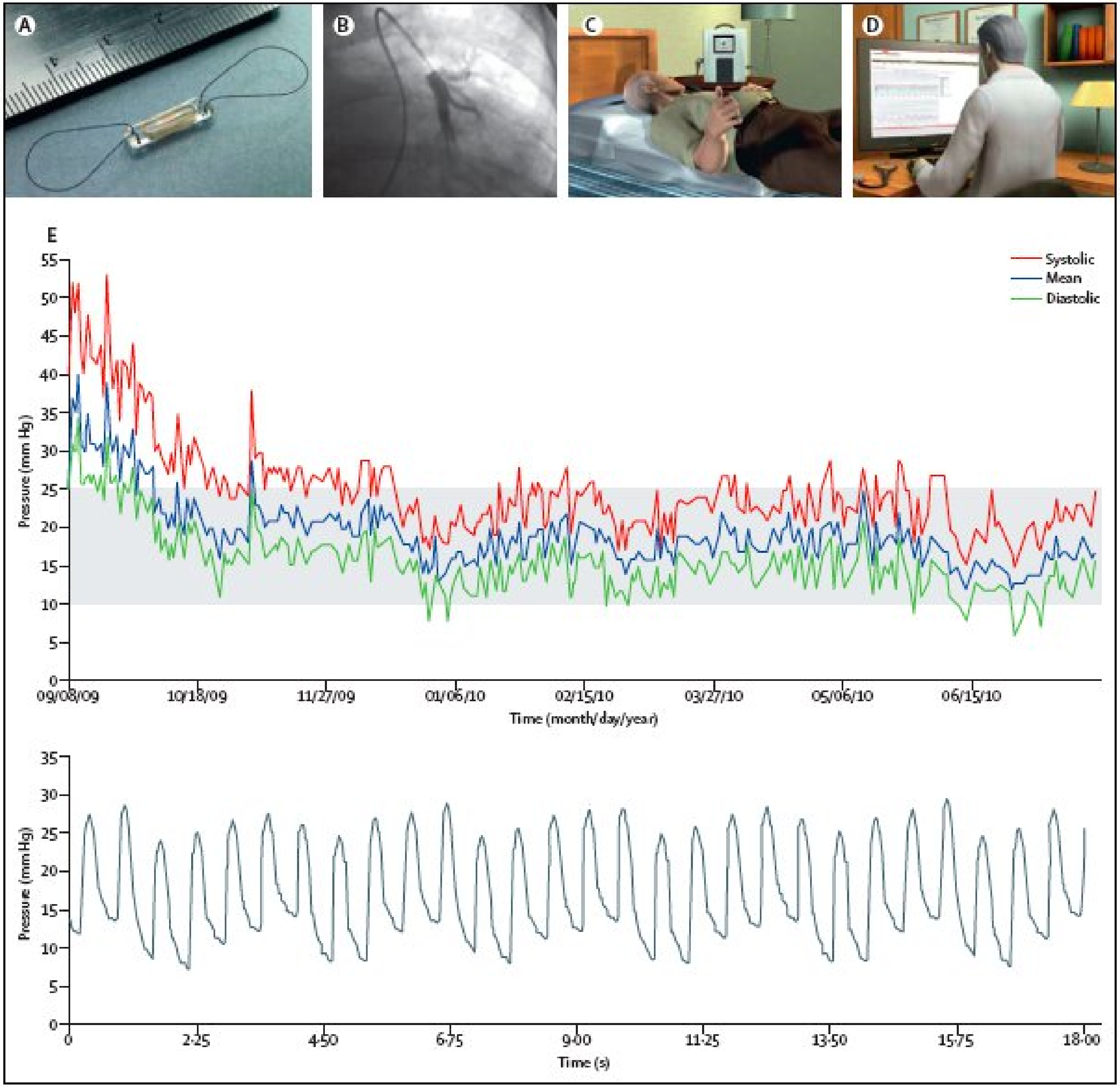


Figure 1: Implantable haemodynamic monitoring system

(A) CardioMEMS sensor or transmitter. (B) Transcatheter is implanted into a distal branch of the descending pulmonary artery. (C) Patient is instructed to take daily pressure readings from home using the home electronics. (D) Information transmitted from the monitoring system to the database is immediately available to the investigators for review. (E) Transmitted information consists of pressure trend information and individual pulmonary artery pressure waveforms.

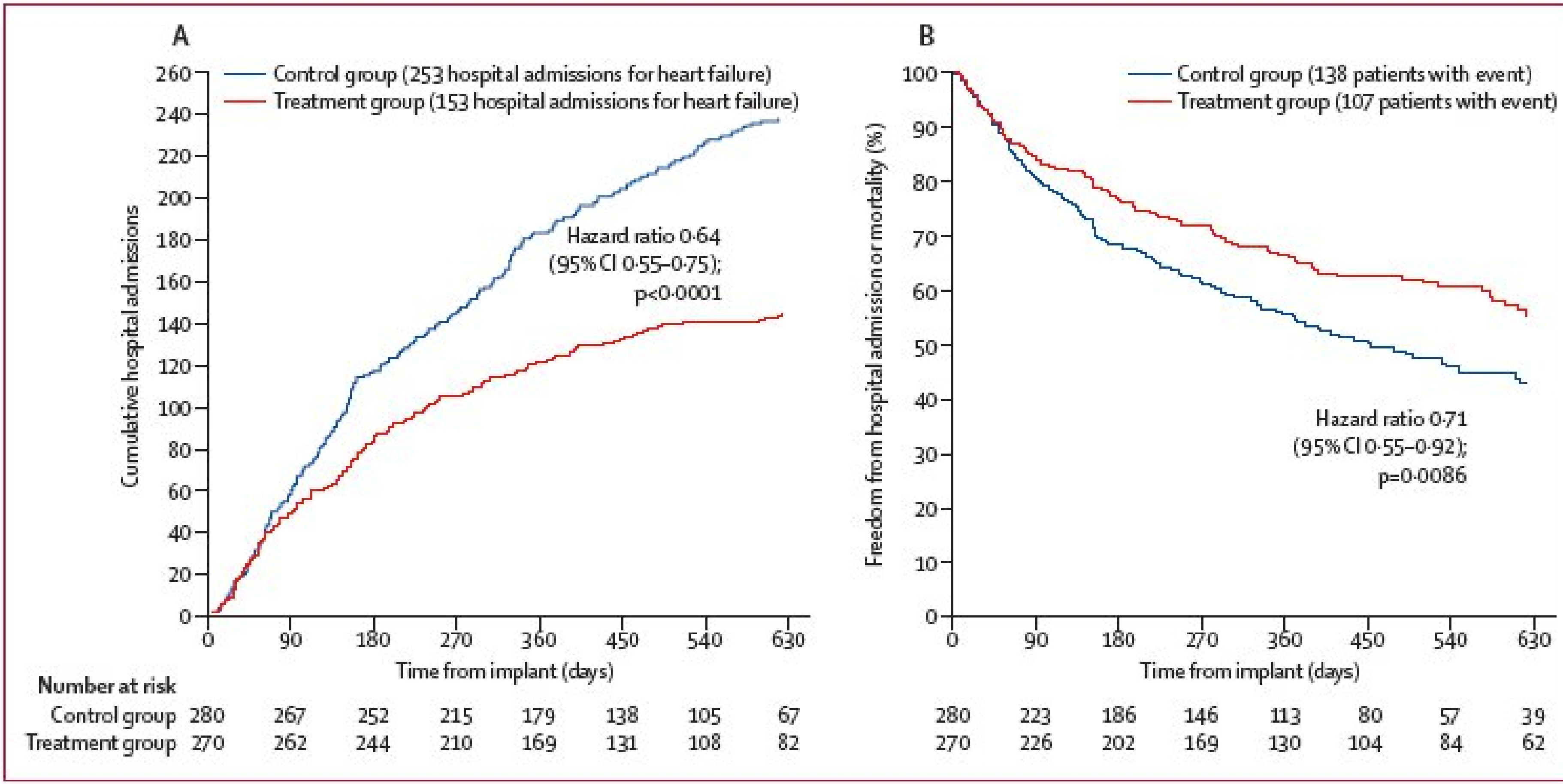


***Figure 3*:** **Cumulative heart-failure-related hospitalisations during entire period of randomised single-blind follow-up (A), and freedom from first heart-failure-related hospitalisation or mortality during the entire period of randomised follow-up (B)**

MILESTONES

2005
Start Remote Monitoring

2010
Learning phase: Remote Monitoring for all brands

2013
Development of organizational model; starting HF Management

2015
ehealth CENTER

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.

Circulation: Heart Failure

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.

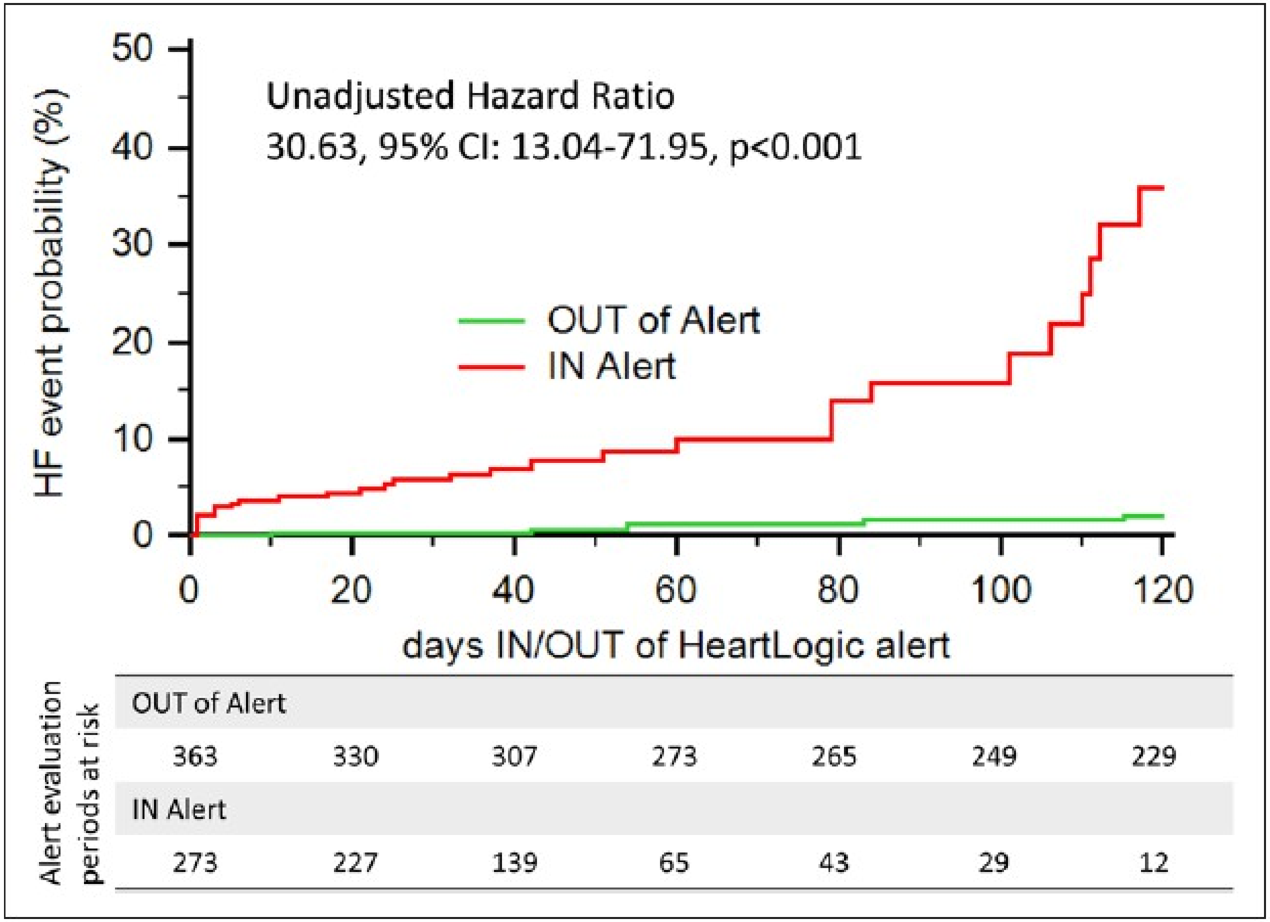
MultiSENSE: 1.6 alerts/patient-year
Capucci et al.: 0.99 alerts/patient-year
Santini et al.: 0.93 alerts/patient-year

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



- 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)

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.

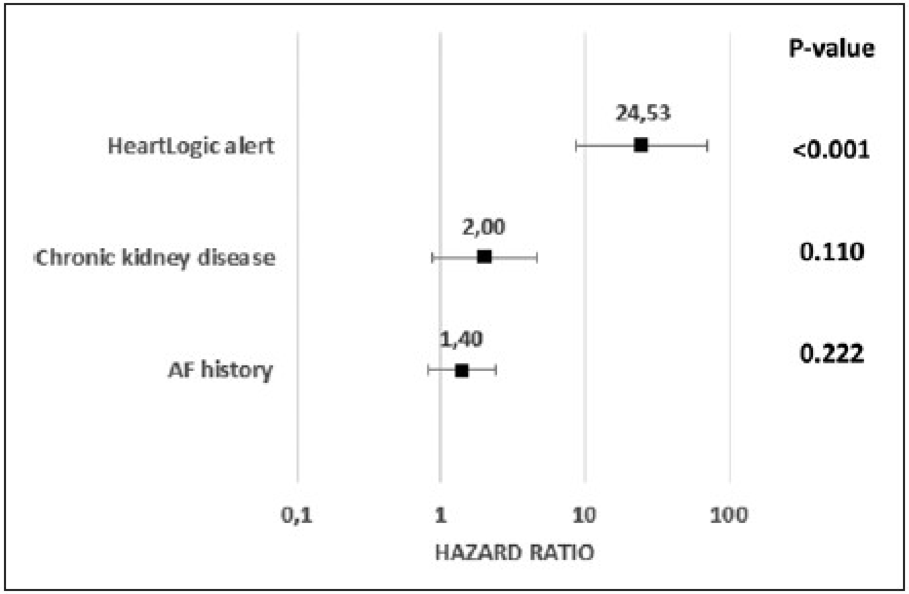


Figure 2. Multivariate analysis.
Patients had a 24.53-fold increased risk of an heart failure event after HeartLogic alert, after adjusting for clinical variables. AF indicates atrial fibrillation.

Results

Alert Management and Association With Heart Failure Events

Of the 273 HeartLogic alerts:

- **204** (75%) were **managed remotely** (no extra in-office visit)

No differences in event rates were noted between **in-office and remote** alert management (*Figure 4B*).

- **107** (39%) were **associated with symptoms of HF** worsening (at the time of the first remote examination)

The most frequent symptoms reported were:

- ✓ worsening of dyspnea on effort or at rest in 93 (87%)
- ✓ fatigue in 65 (61%)
- ✓ orthopnea in 22 (21%)

The **presence of HF symptoms** at the time of HeartLogic threshold crossing was associated with a **higher risk of HF events**(*Figure 4C*).

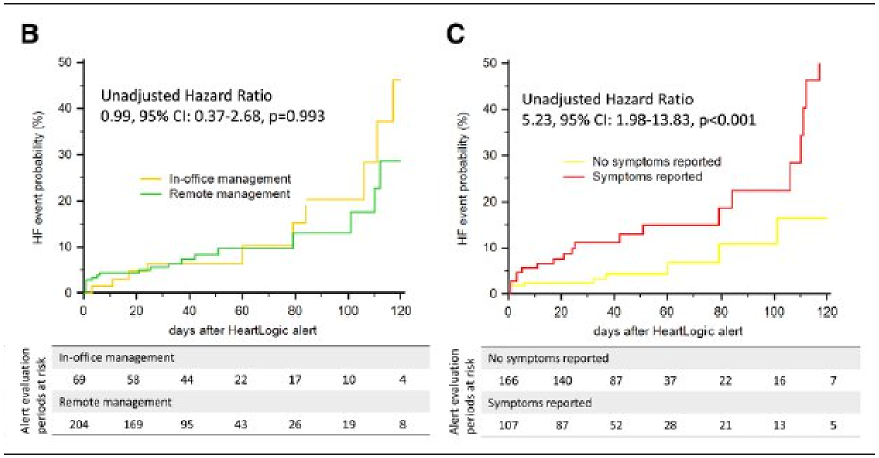


Figure 4: Kaplan-Meier curves for time to first heart failure (HF) event.

Results

❑ **117** (43%) **triggered clinical actions:**

The most frequent actions taken to manage the HF condition detected by the alert were (multiple actions per alert):

- ✓ 66% diuretic dosage increase
- ✓ 34% other drug adjustment
- ✓ 6% patient education on therapy adherence
- ✓ 3% device reprogramming

Santini et al.: 43%

Taking clinical actions in response to the HeartLogic alert was associated with a **lower risk of HF events**(*Figure 4A*).

A possible bias: HF events occurred early after the alert, which may not have allowed any action to be taken. A new analysis was performed starting at day 7 (weekly re-alert notification).

The result was confirmed, with a lower rate of events associated with alerts followed by clinical actions: HR, 0.34 (95% CI, 0.12–0.96), *P*=0.047

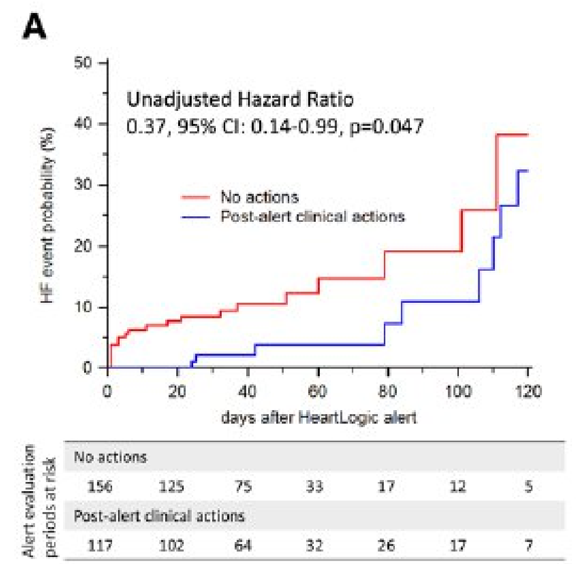


Figure 4: Kaplan-Meier curves for time to first heart failure (HF) event.

Conclusions

- HeartLogic is able to identify patients during periods of significantly increased risk of heart failure events.

  → The use of HeartLogic may enable an **efficient use of healthcare resources** for the management of patients with HF (the time IN alert state is much shorter than that of OUT of alert state periods).

- When clinical actions are undertaken in response to alerts, the rate of heart failure events seems lower.

  → The rate of alerts is low, and this would **not generate a high workload** at the centers in case an alert based management strategy was adopted.

- The absence of an in-office visit after a HeartLogic alert did not impair the patient's outcome.

  → **HeartLogic alerts may be safely managed remotely**, without increasing the workload of the clinic.

- The presence of symptoms at the time of HeartLogic alert was associated with a higher risk of HF events.

  → **Verification of symptoms** seemed useful to better stratify patients at risk of HF events.

Conclusions

Comparison with other studies

	RELATIVE RISK of HF event	
PARTNERS-HF (Whellan et al. 2010)	5.5 times (positive HF diagnostic algorithm Vs negative HF diagnostic algorithm)	TRIAGE-HF Algorithm
TRIAGE-HF development* (Cowie et al. 2012)	10 times (High vs Low risk score)	TRIAGE-HF Algorithm
MORE-CARE (Burri et al. 2018)	6.3 Times (High vs Low risk score)	TRIAGE-HF Algorithm
MultiSENSE (Gardner et al. 2018)	22 Times (HL IN alert state Vs HL<2)**	HeartLogic Algorithm
HeartLogic Italian Group (Calò et al. 2021)	24 Times (HL IN alert state Vs HL out of alert state)	HeartLogic Algorithm

The algorithm evaluated by Cowie and Burri is **not equipped with an alert**, and periodic evaluations are needed to assess the risk status.

** Data from different study: PARTNERS-HF, SENSE-HF, Italian Clinical Service Project, OFISSER, CONNECT, FAST and PRECEDE-HF*
*** Similar condition of TRIAGE-HF*

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

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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.

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Derivazione dell'algoritmo

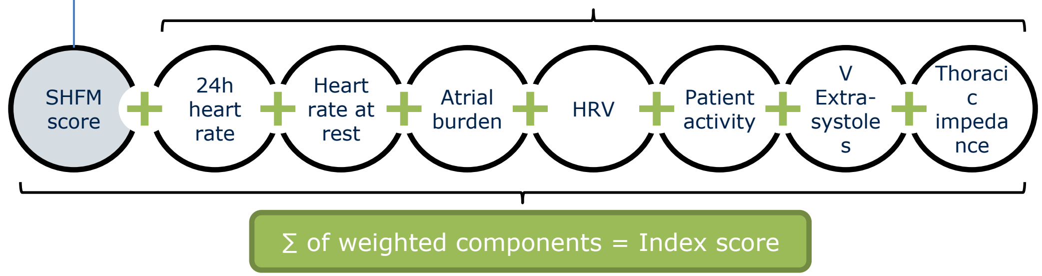
Risultati analisi cross-sectional

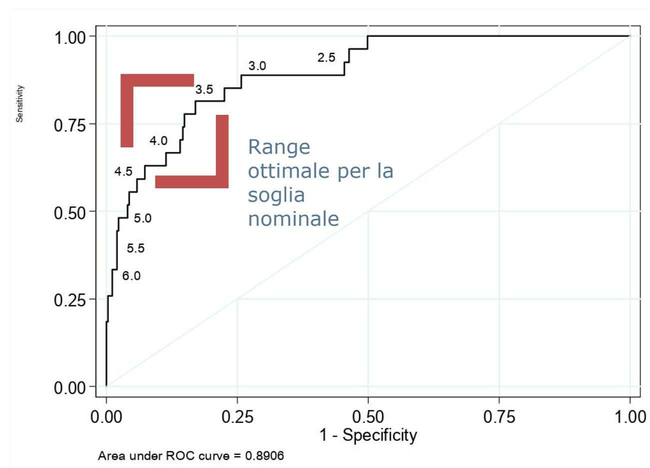
Modelli logistici univariati

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

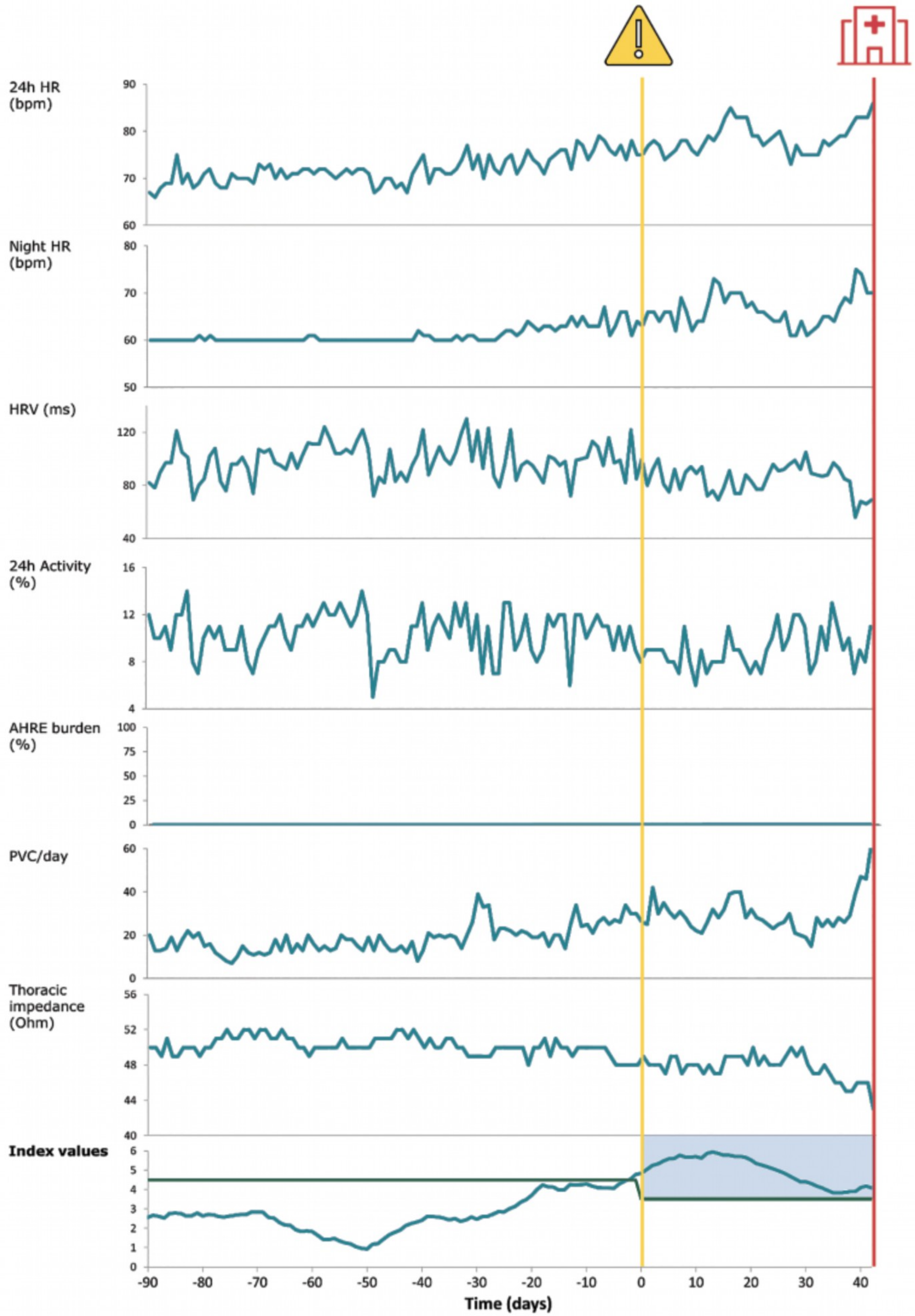




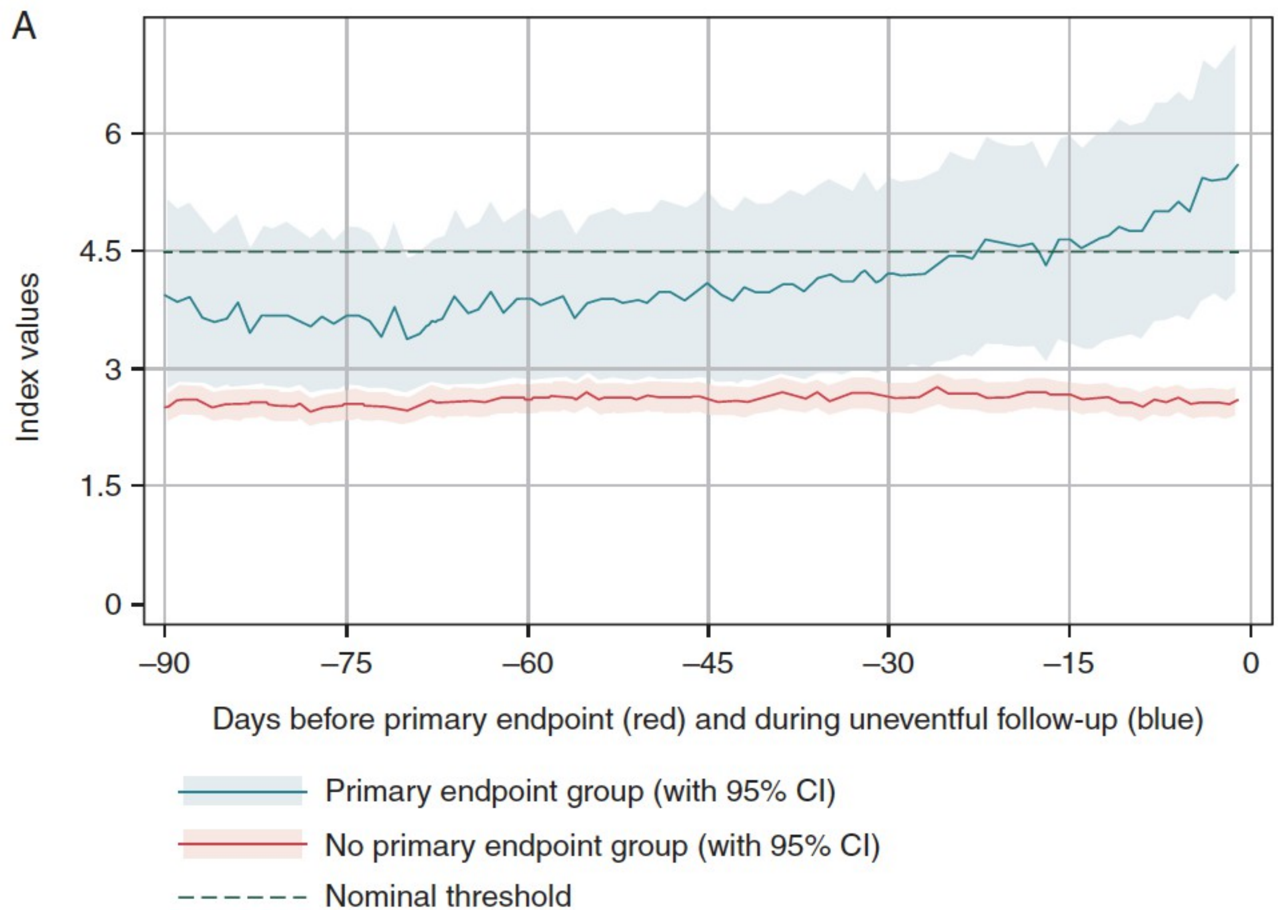
Rischio per incremento unitario del valore dell'indice
OR, 2.73 (1.98-3.78), p<0.001

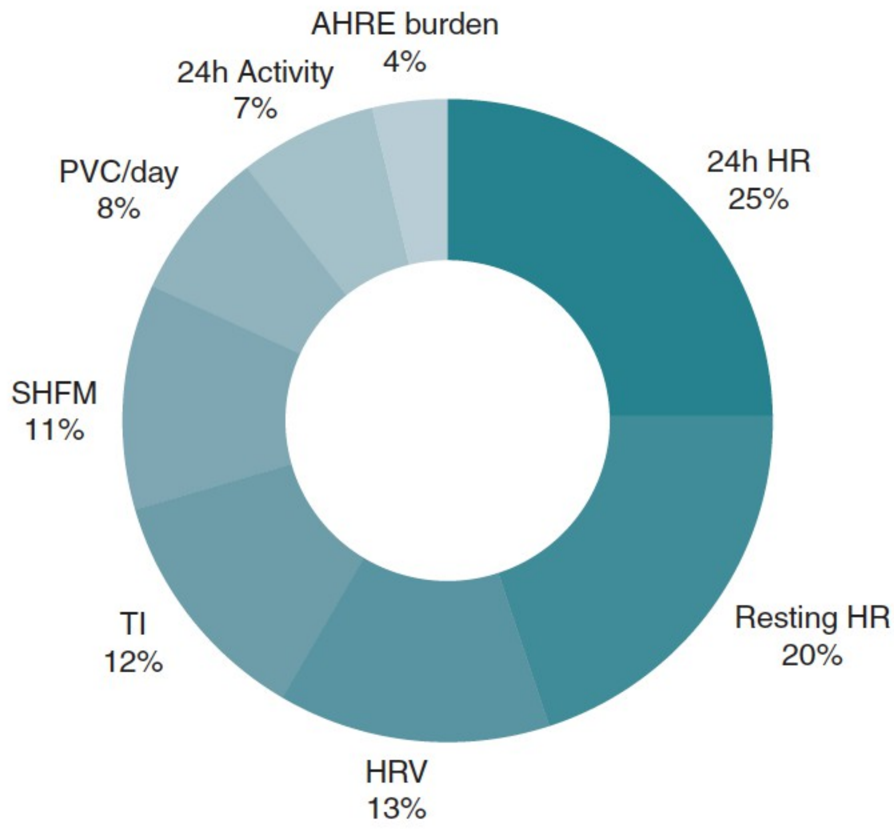
Area sotto la curva ROC
0.89 (95%CI, 0.83-0.95)

Nominal Threshold (NT) ottimale
Range: 3.5 – 4.5



24h HR (bpm)
Night HR (bpm)
HRV (ms)
24h Activity (%)
AHRE burden (%)
PVC/day
Thoracic impedance (Ohm)
Index values
Time (days)

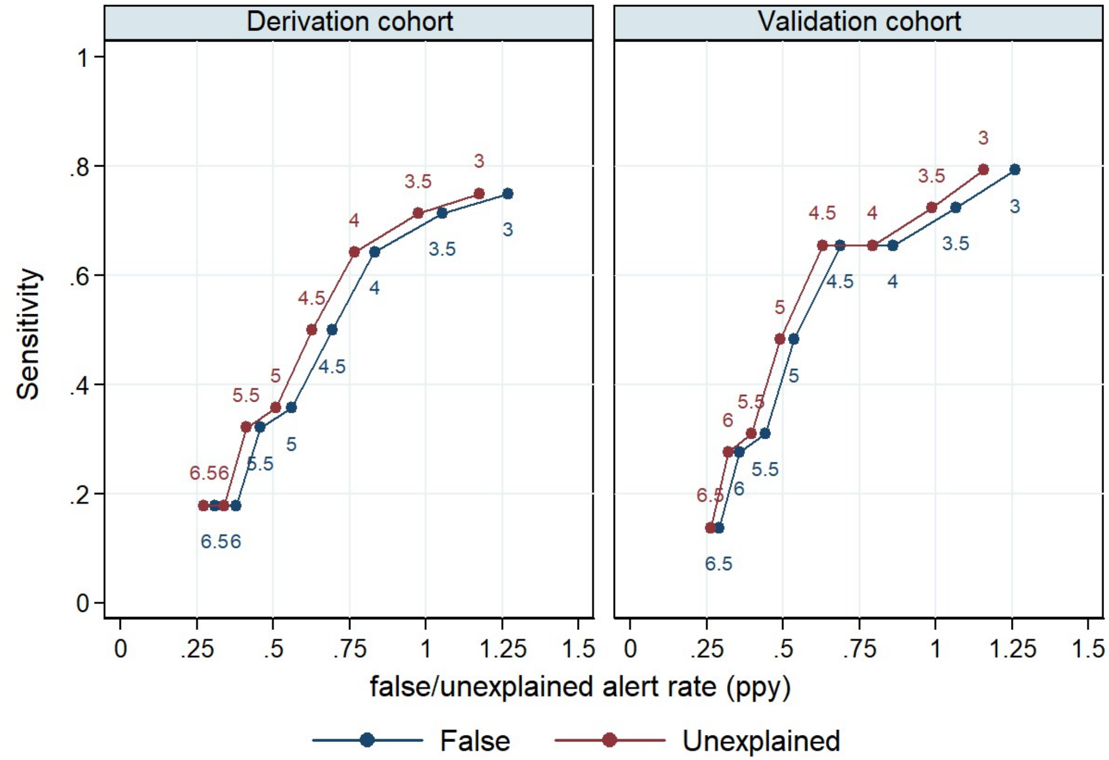

A
Index values
6
4.5
3
1.5
0
–90
–75
–60
–45
–30
–15
0
Days before primary endpoint (red) and during uneventful follow-up (blue)
Primary endpoint group (with 95% CI)
No primary endpoint group (with 95% CI)
Nominal threshold



The relative contribution of all seven components to the index value, averaged for the last 7 days before 60 primary endpoint events

Validazione dell’algoritmo

Curve ROC modificate (sensibilità vs. tasso di allarme falso/unexplained) nel gruppo di derivazione e validazione

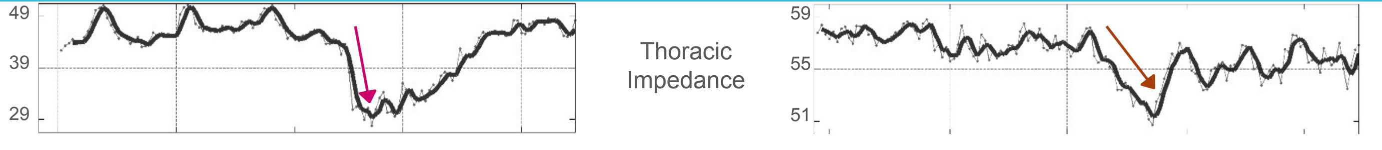


L’indice performava in modo simile nei due gruppi
In relazione alla soglia NT selezionata, la sensibilità aumentava con il tasso di allarmi falsi/unexplained
Anche con una sensibilità massimo dell’80%, il tasso di allarmi unexplained non superava mai 1.25 per paziente-anno

Benefit of Multifactorial Approach

Patient A — *Two Observed Cases* — **Patient B**

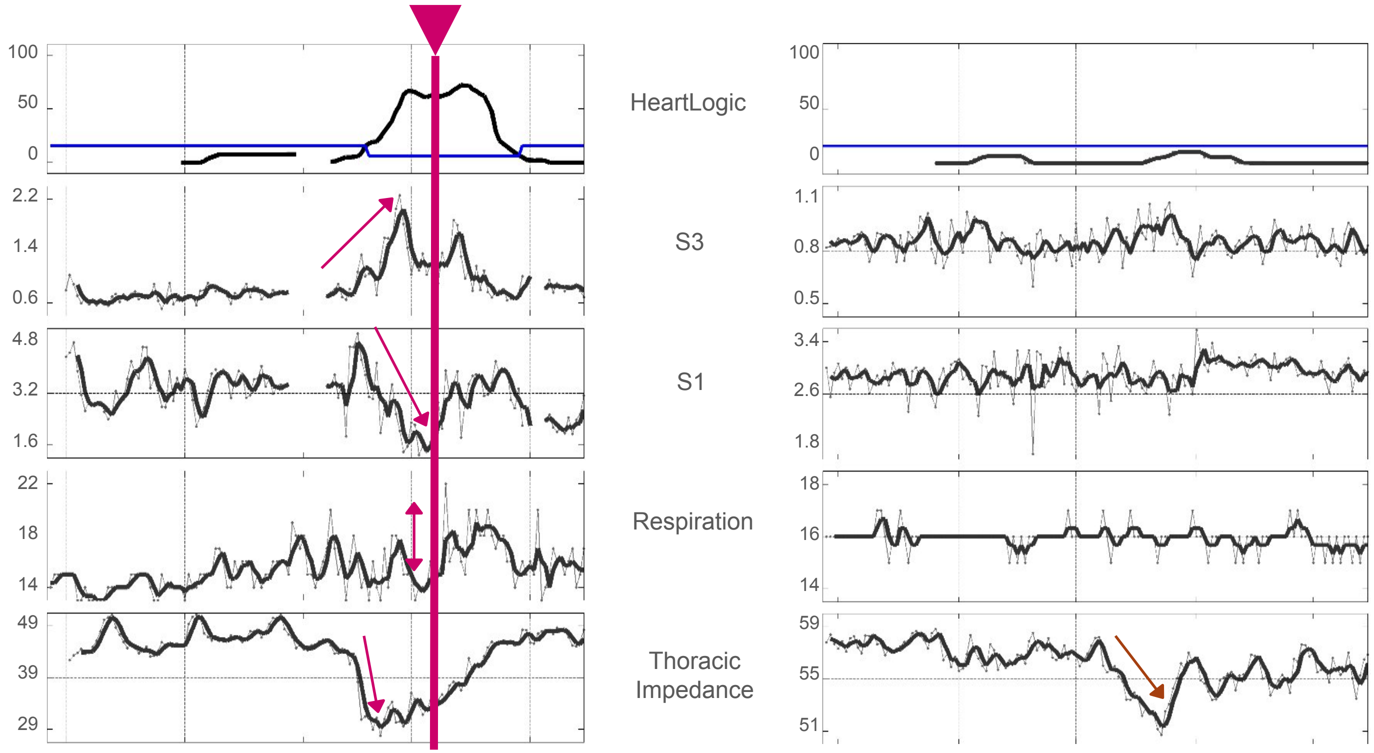
Which patient had a Heart Failure Event?



Benefit of Multifactorial Approach

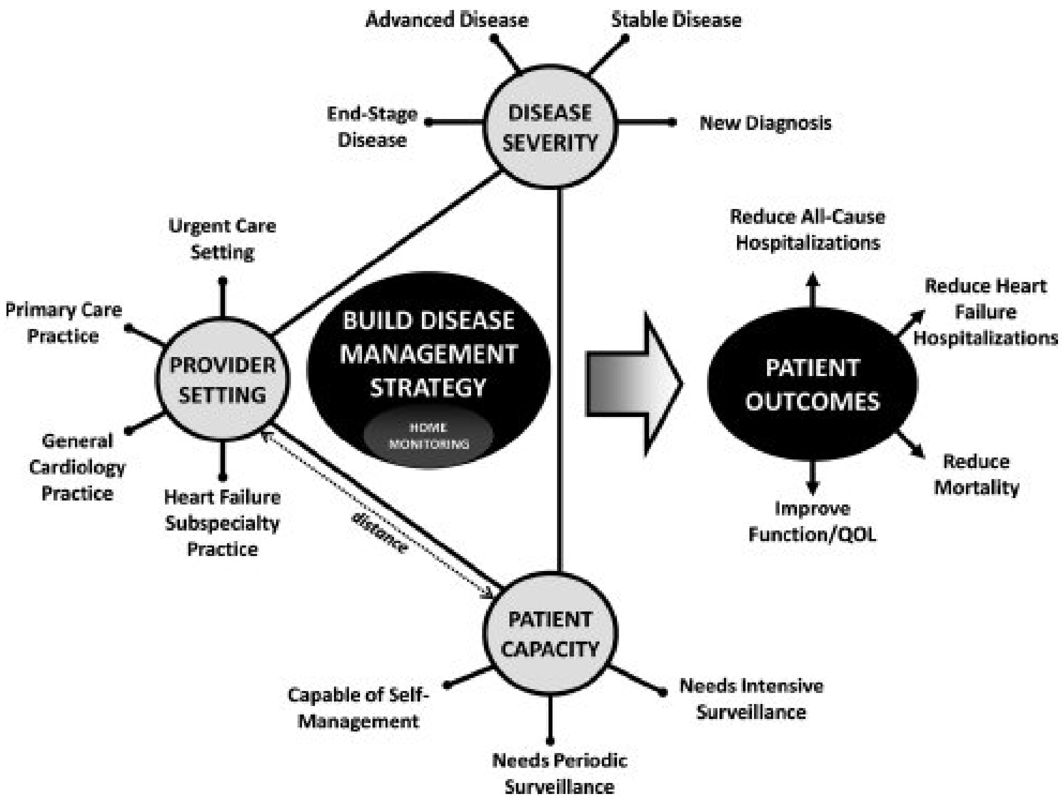
Patient A — *Two Observed Cases* — **Patient B**

Multi-sensor Changes before a **HF Event** | Impedance-only Change with **NO** Event

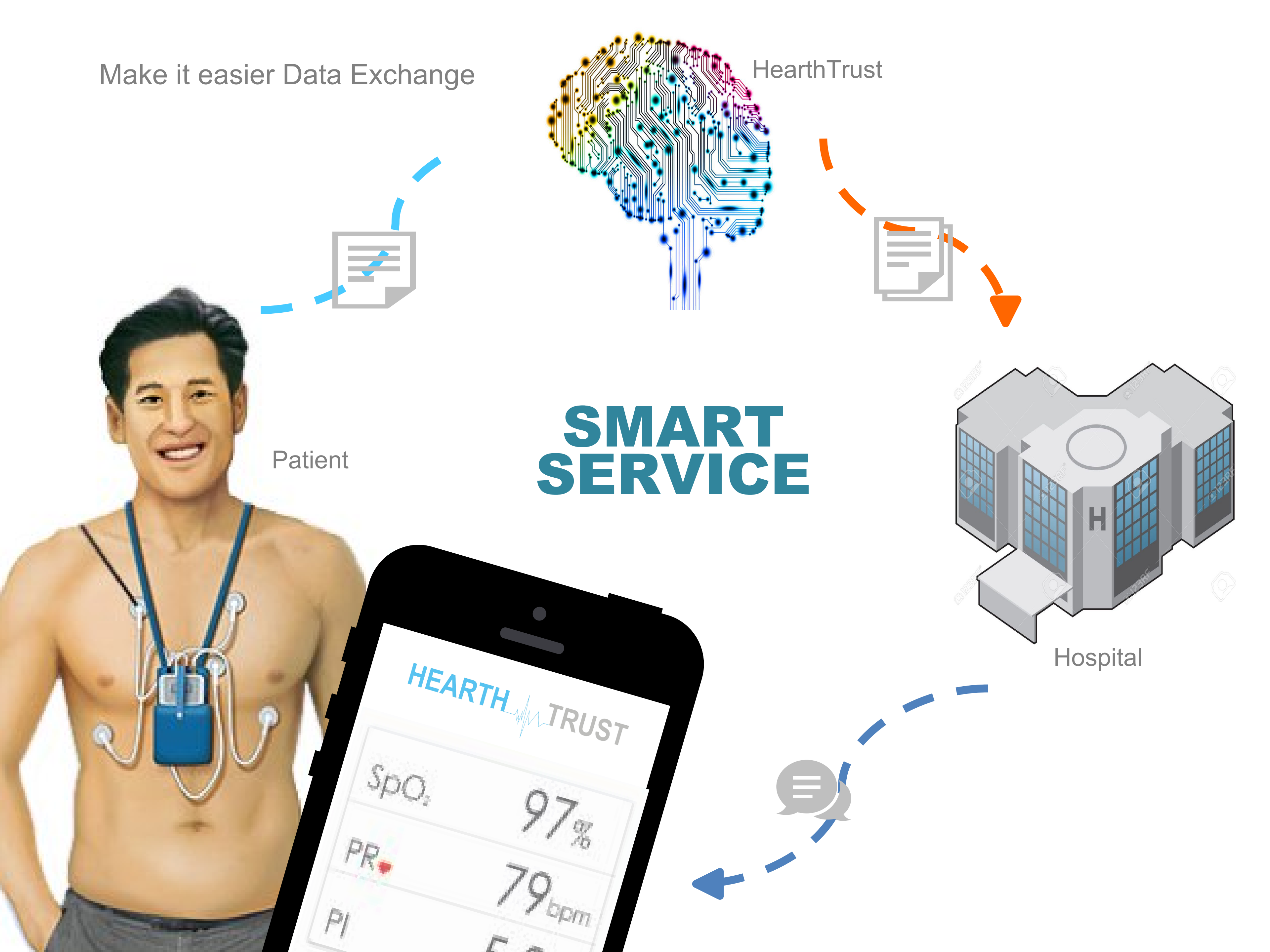


PROCESS CONTROL

DESAI AS, CIRCULATION 2012



IL PAZIENTE
LA TECNOLOGIA


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


Science
Translational
Medicine
28 FEBRUARY 2018
AAAS

WEARABLES

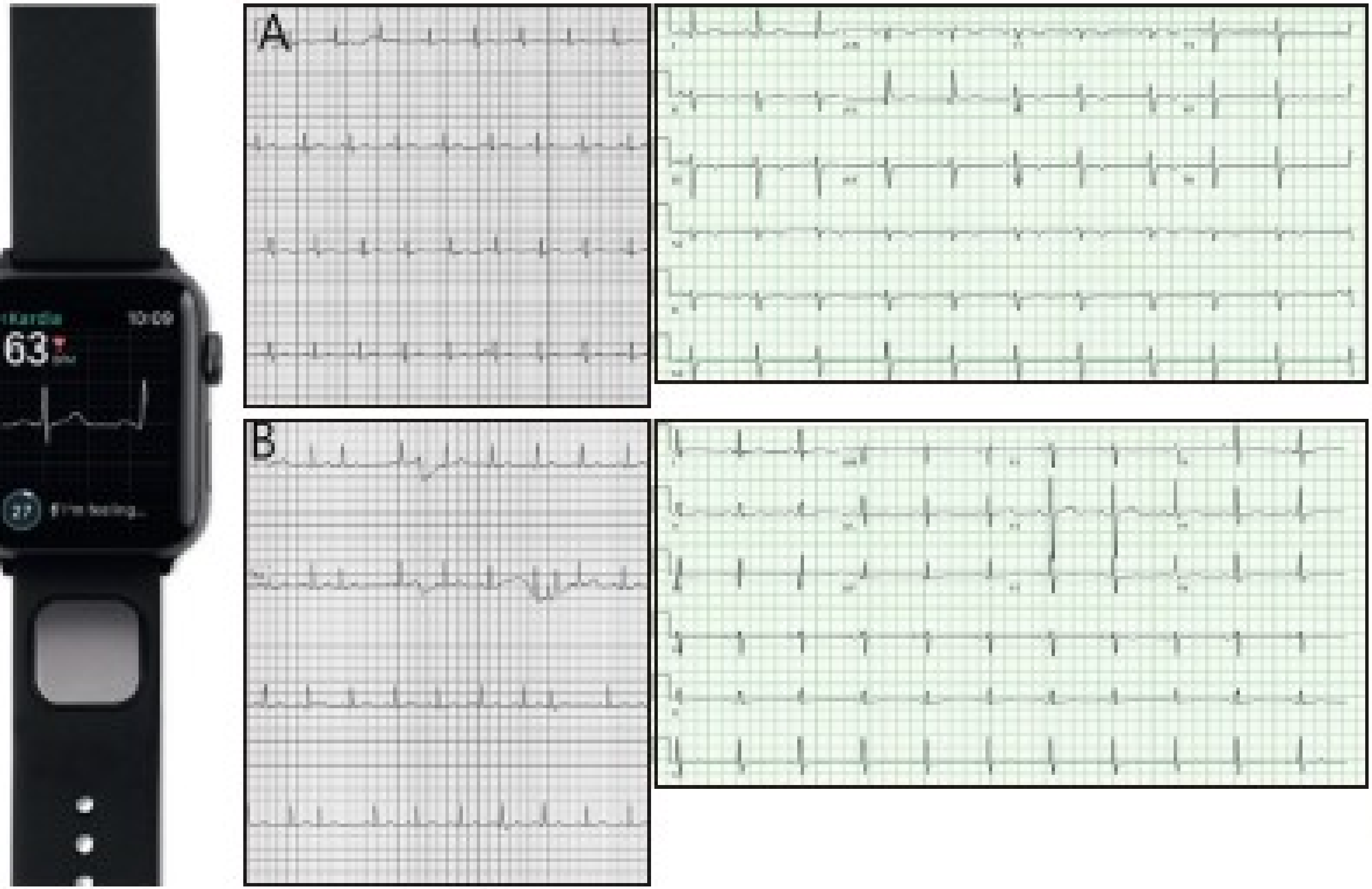
- FOR FIT
- FOR RUN
- FOR TECH SAVVY
- FOR HEALTH

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**


Kardia
10:09
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′
Today
Health Data
Sources
Medical ID


Health Data
Heart
Favorites
Heart Rate
51–163 BPM
Resting Rate
59 BPM
Walking Average
79 BPM
Workout
105–163 BPM
Breathe
MAX
163
MIN
51
105

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.

L'OSPEDALE
LA TECNOLOGIA

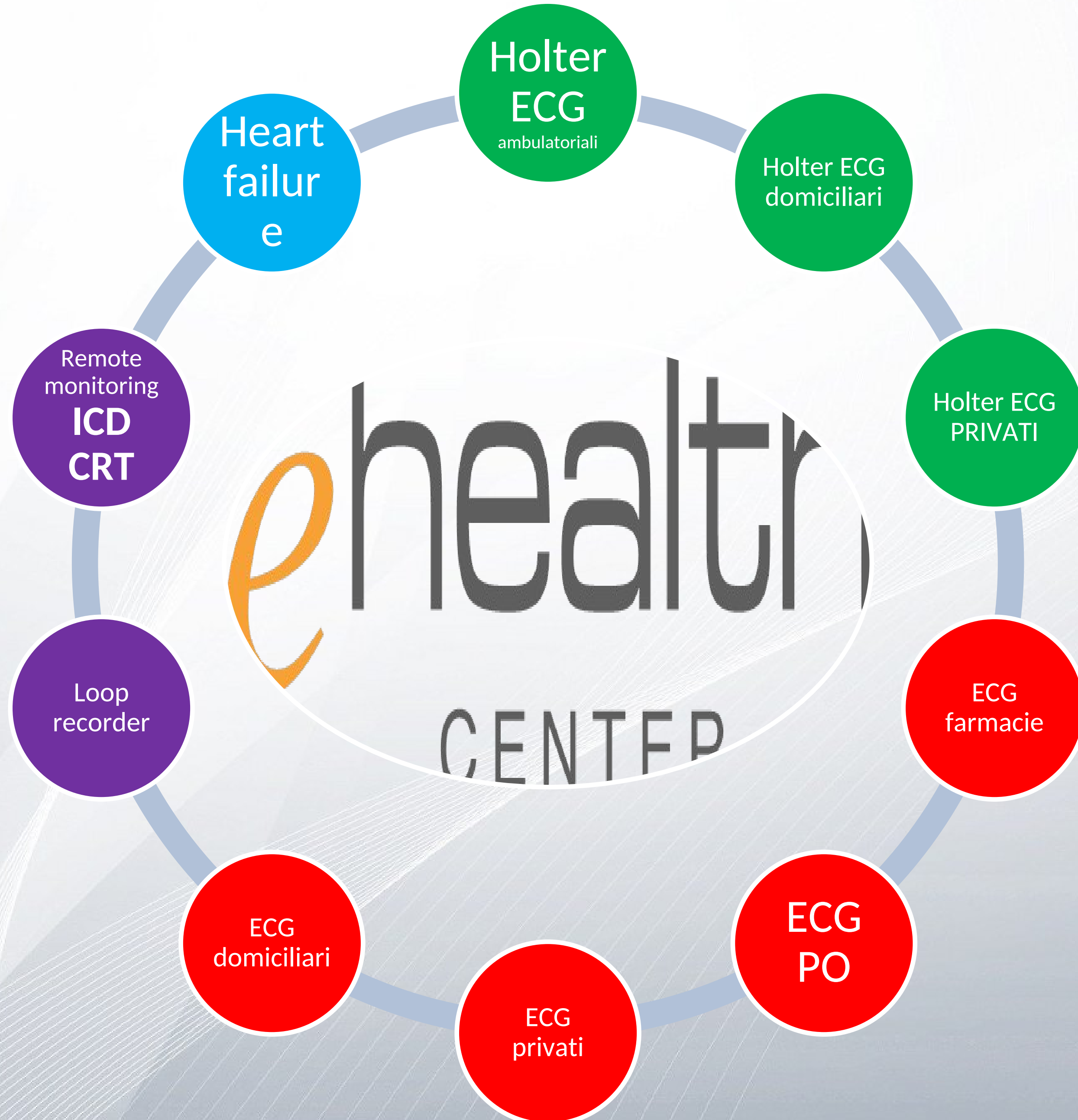
PAZIENTI E CAREGIVERS

REPARTO e AMBULATORIO CARDIOLOGIA

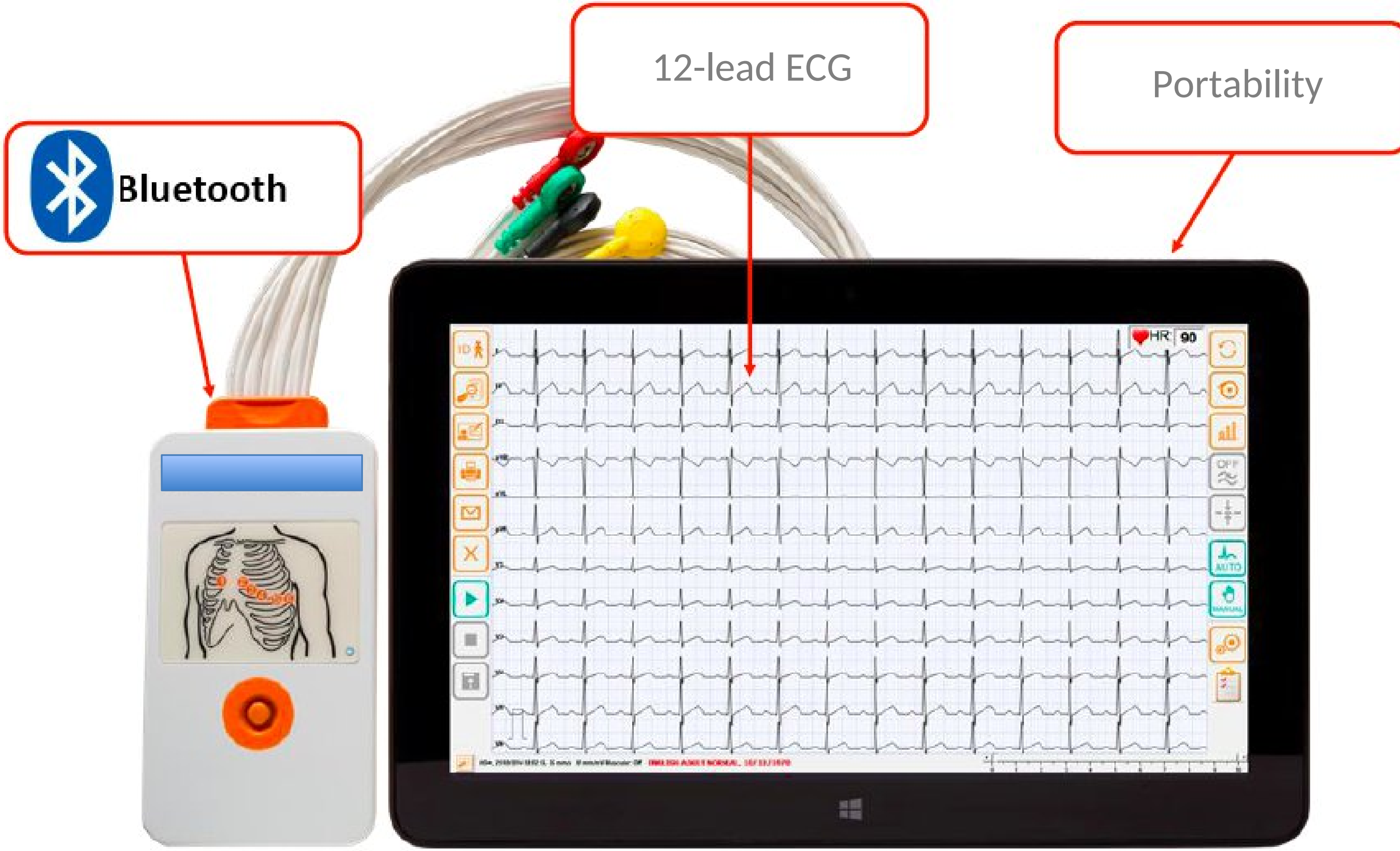
Preospedalizzazione

Servizi domiciliari

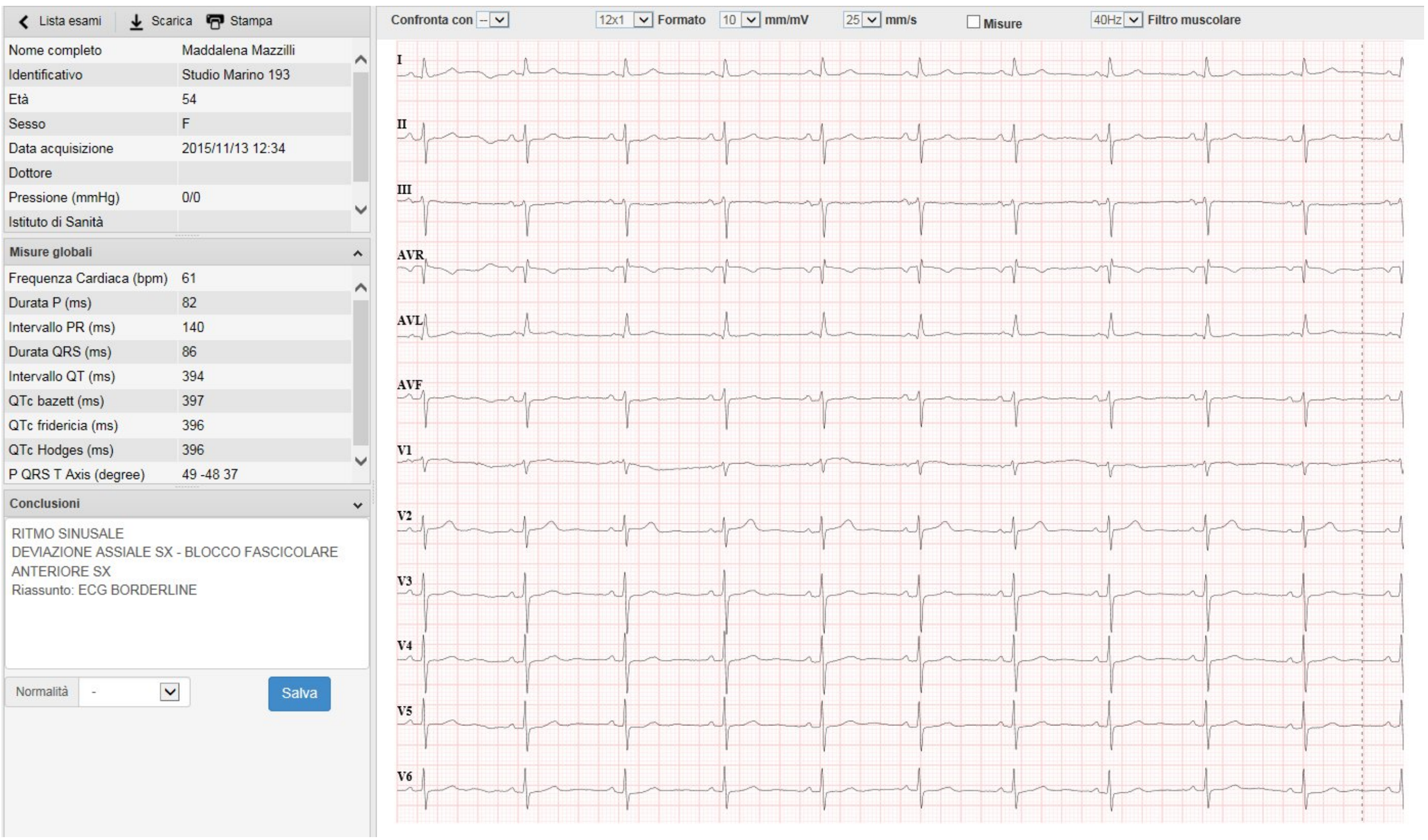
PS



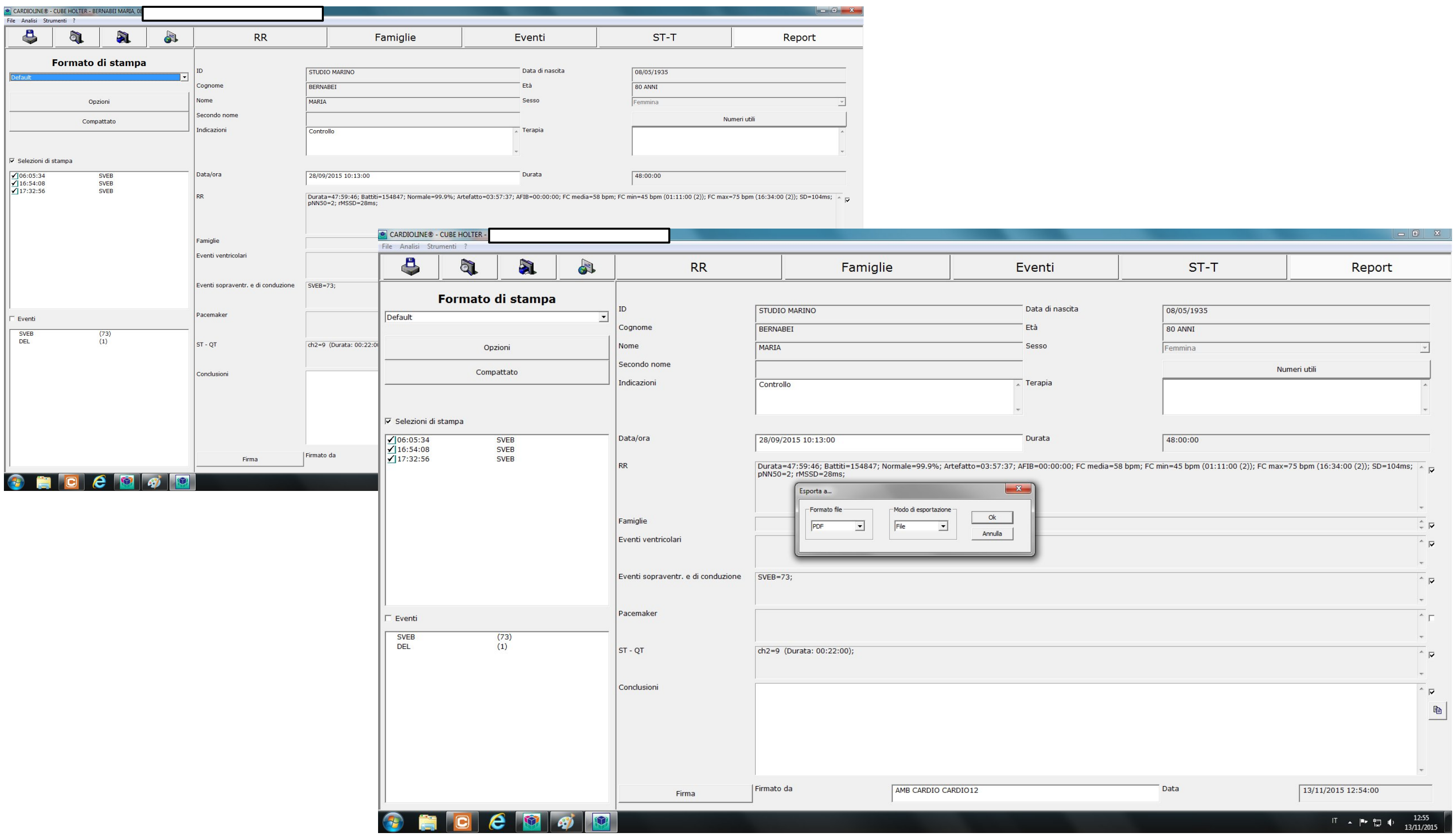
Team: 14 cardiologi, 7 tecnici, 2 infermieri

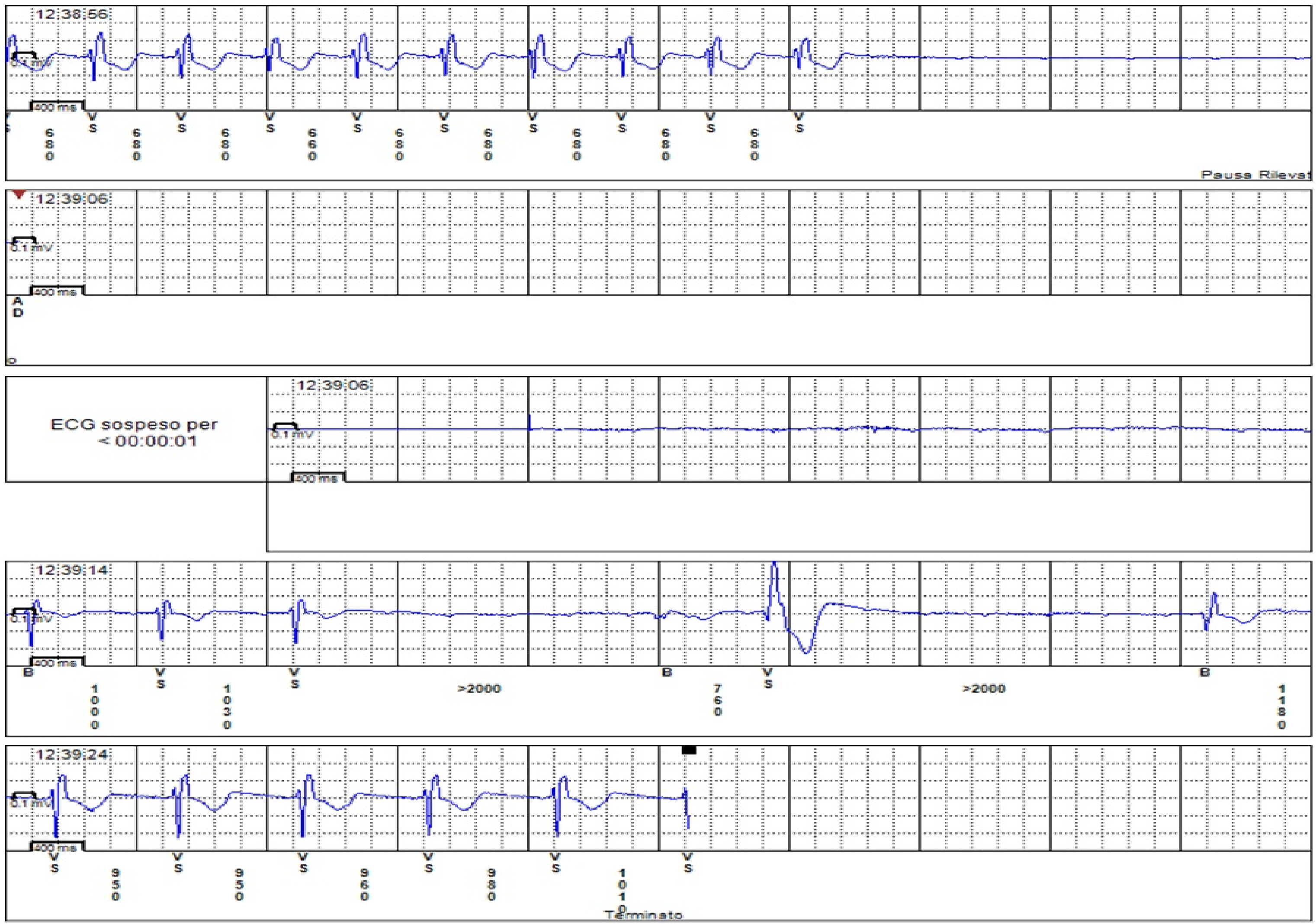

Bluetooth
12-lead ECG
Portability

ONLINE ECG ANALYSIS



REMOTE HOLTER ECG




12:38:56
0.1 mV
400 ms
Pausa Rilevat
12:39:06
A
D
ECG sospeso per
< 00:00:01
12:39:14
>2000
12:39:24
Terminato

ORGANIZATION

DUTIES
OF THE TECHNICIANS AND DOCTOR

REVEAL MANAGEMENT FLOW CHART

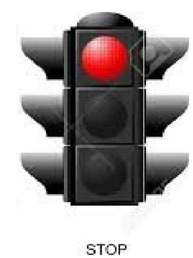
Daily check of scheduled transmission by nurse and technician
+ CareAlert
Check missing transmissions

Transmission with event:
Pause
Atrial arrhythmias
Ventricular arrhythmias
Bradycardia

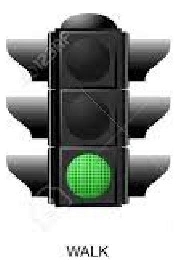
Technician

1. Print relevant information of transmission
2. Print patient last follow-up
3. Drug terapy
4. Fill a specific sheet on Cardiomanagement tool
5. Submit transmission to physician
6. Register all actions done by physician on a specified sheet

Physician



1. Review printed information
2. Classify transmission
3. Establish what to do (call the patien, schedule an in office visit, change drug therapy)



Transmission without event

Technician

1. Fill in a record in an Excel DB

LIGHTHOUSE APPLICATION

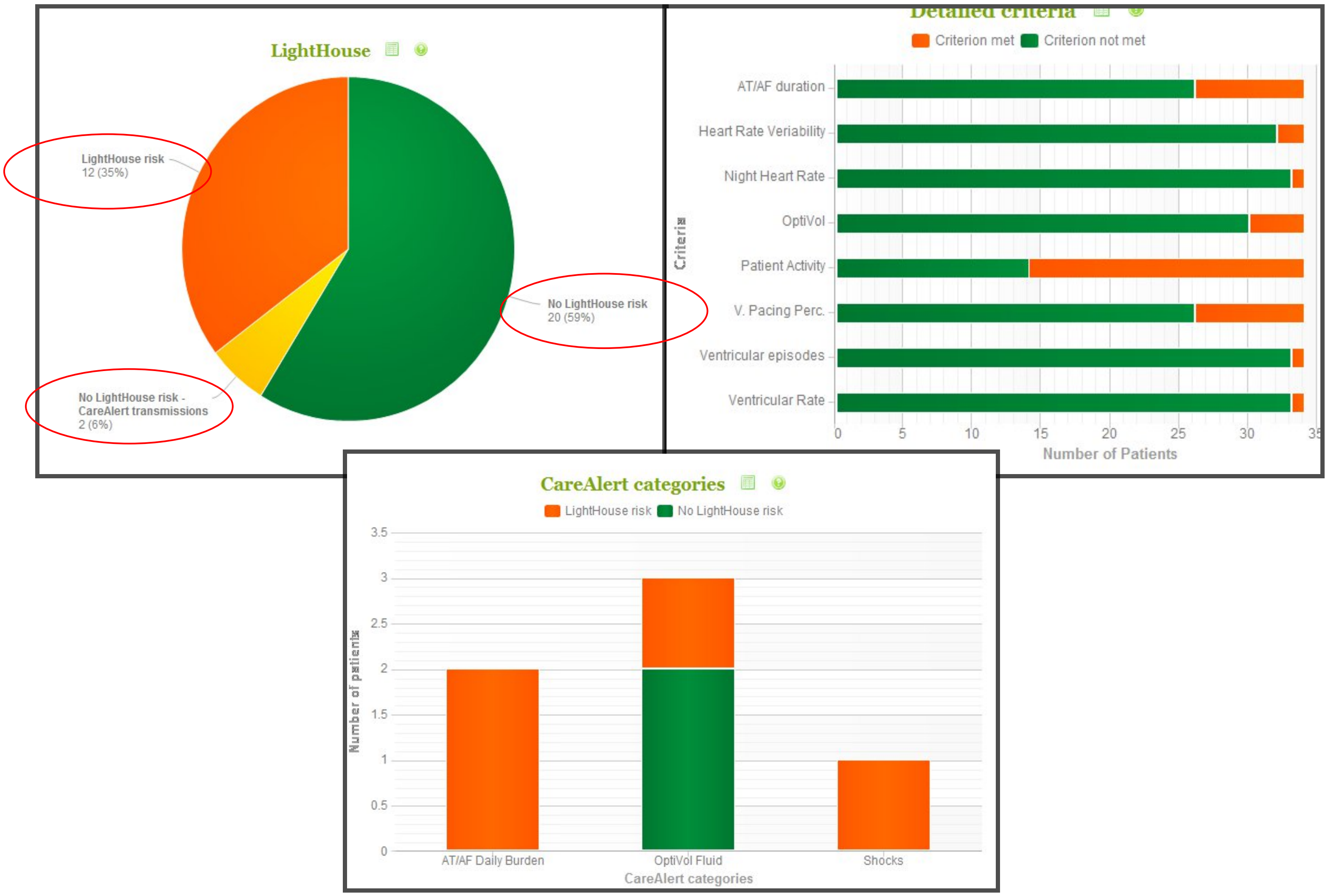
#	Device serial number	Transmission date/Time	CareAlert transmission	LightHouse risk	Risk score (0-1)	AT/AF duration evidence	Ventricular Rate evidence	OptiVol evidence	Heart Rate Veriability evidence	Night Heart Rate evidence	V. Pacing Perc. evidence
1	PZC605348S	05-11-2013 03:35	No	Yes	1	Yes	Yes	No	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



Artificial Intelligence in Cardiology

Kipp W. Johnson, BS,[a,b] Jessica Torres Soto, MS,[c,d,e] Benjamin S. Glicksberg, PhD,[a,b,f] Khader Shameer, PhD,[g] Riccardo Miotto, PhD,[a,b] Mohsin Ali, MPhil,[a,b] Euan Ashley, MBChB, DPhil,[c,d,e] Joel T. Dudley, PhD[a,b]

ABSTRACT

Artificial intelligence and machine learning are poised to influence nearly every aspect of the human condition, and cardiology is not an exception to this trend. This paper provides a guide for clinicians on relevant aspects of artificial intelligence and machine learning, reviews selected applications of these methods in cardiology to date, and identifies how cardiovascular medicine could incorporate artificial intelligence in the future. In particular, the paper first reviews predictive modeling concepts relevant to cardiology such as feature selection and frequent pitfalls such as improper dichotomization. Second, it discusses common algorithms used in supervised learning and reviews selected applications in cardiology and related disciplines. Third, it describes the advent of deep learning and related methods collectively called unsupervised learning, provides contextual examples both in general medicine and in cardiovascular medicine, and then explains how these methods could be applied to enable precision cardiology and improve patient outcomes.
(J Am Coll Cardiol 2018;71:2668–79) © 2018 The Authors. Published by Elsevier on behalf of the American College of Cardiology Foundation. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

Ambulatorio scompenso
Medici- Infermieri -Tecnici (controllo device e sonographer)
Gestione a distanza dei pazienti – Contatto telefonico con care givers
Rapporto con I medici invianti (specialisti e MMG)

↕

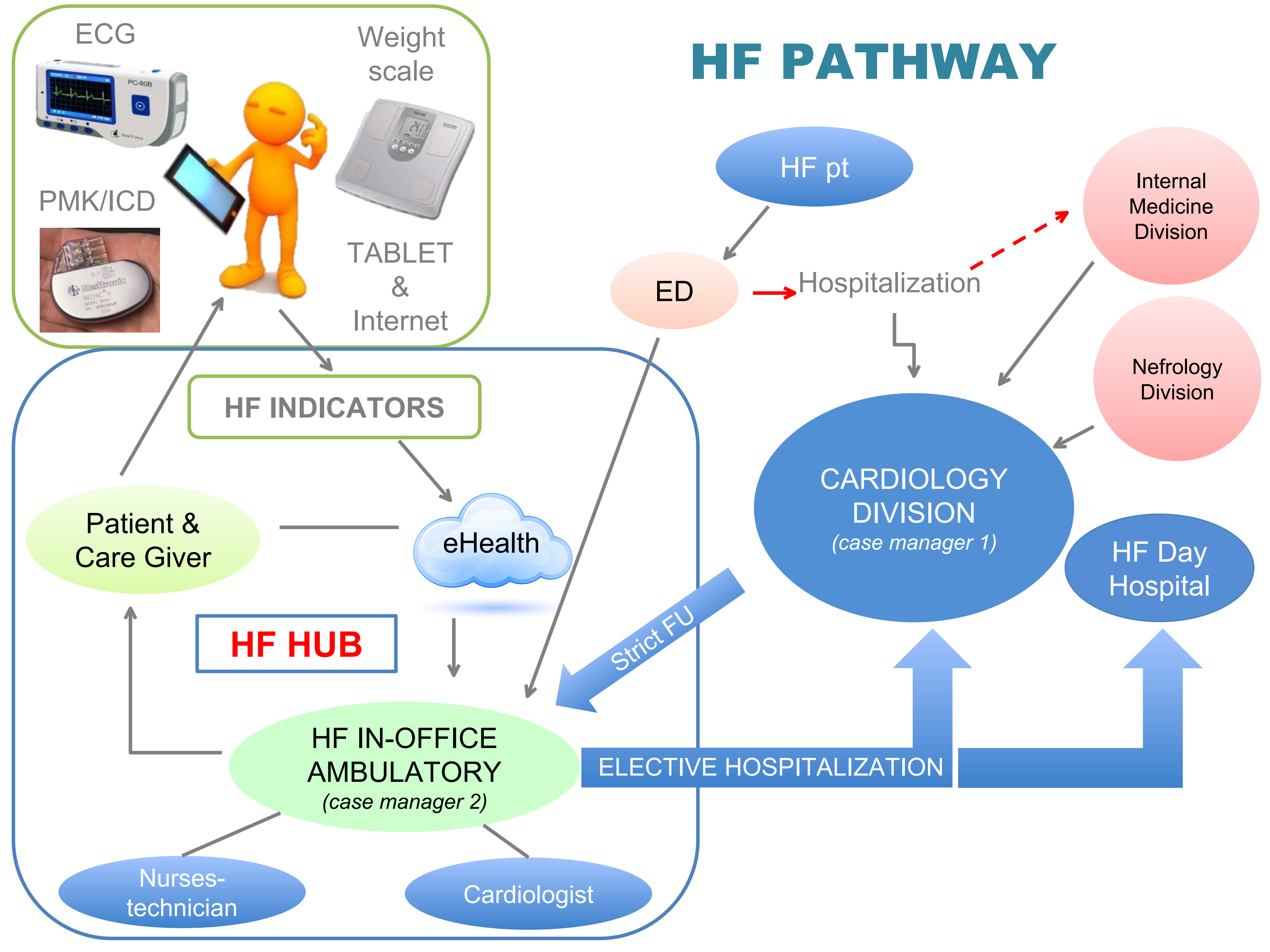
Case Manager in Ambulatorio

↕

Case Manager in Ospedale

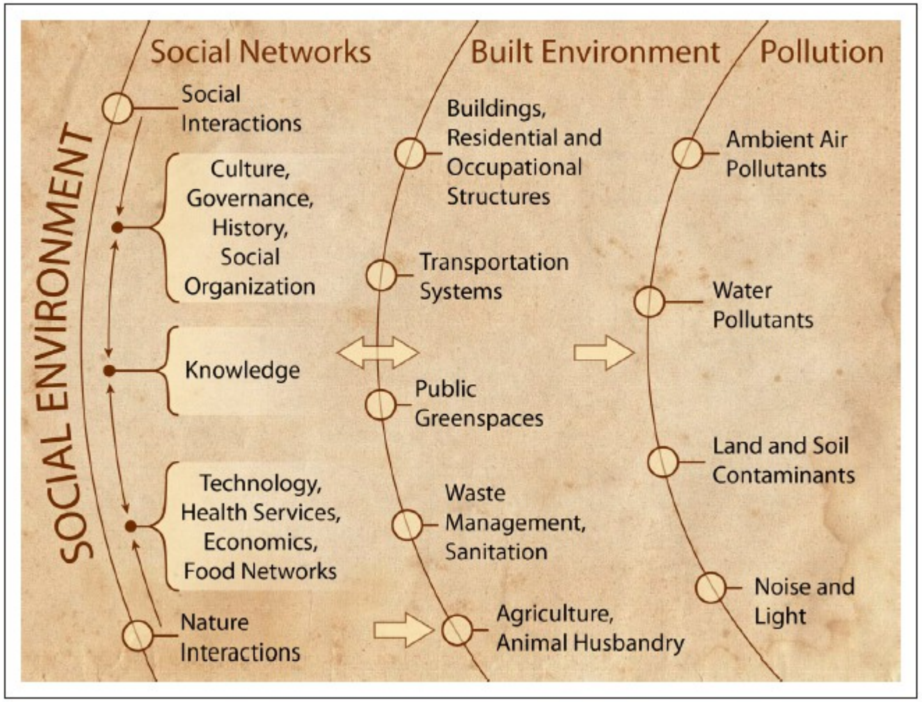
↕

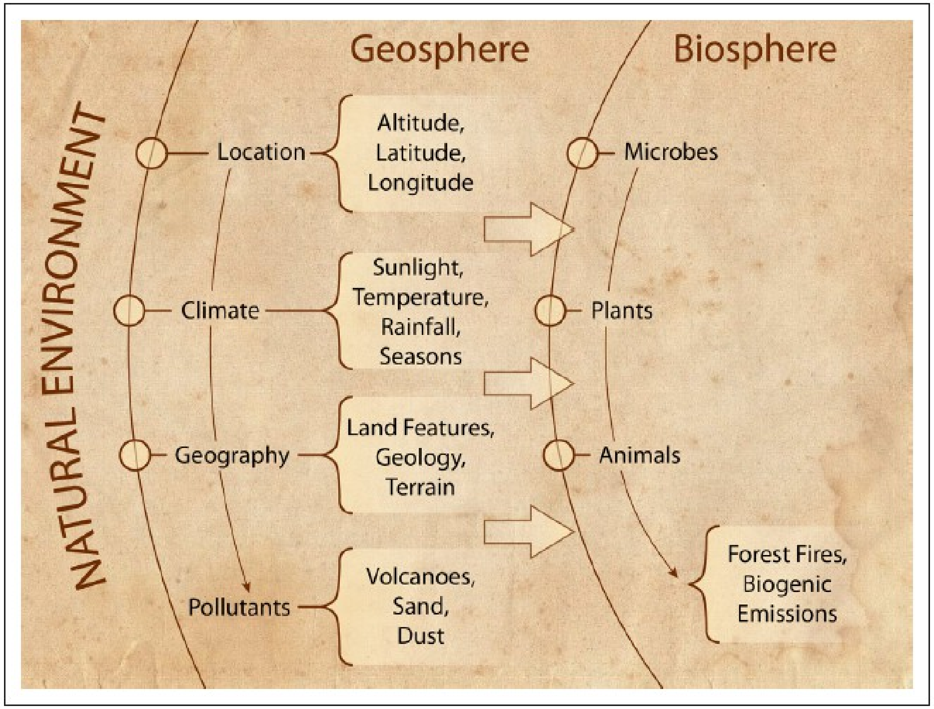
Valutazione paziente in PS – Definizione del percorso più appropriato
Valutazione giornaliera di tutti I pz scompensati ricoverati nei vari reparti
(Medicina Urgenza – Cardiologia- Medicina Interna)
Mobilizzazione del paziente – Contatto telefonico con care givers
Definizione del percorso alla dimissione (domicilio- riabilitazione)
Formazione del paziente (depliant)
Impostazione controllo a distanza

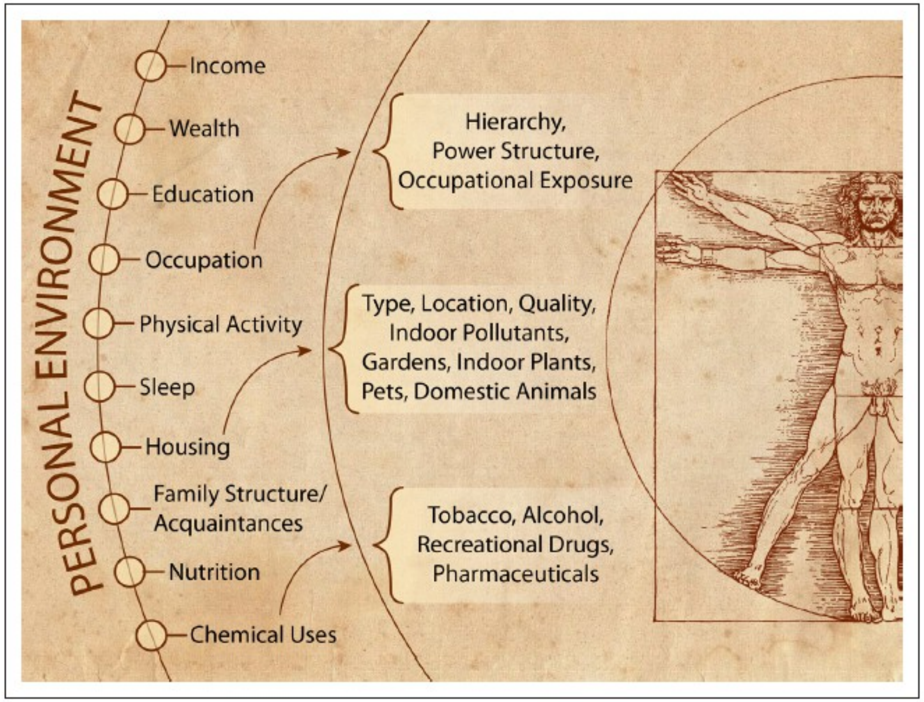


HF PATHWAY
ECG
Weight scale
PMK/ICD
TABLET & Internet
HF INDICATORS
Patient & Care Giver
eHealth
HF HUB
HF IN-OFFICE AMBULATORY
(case manager 2)
Nurses-technician
Cardiologist
HF pt
ED
Hospitalization
Internal Medicine Division
Nefrology Division
CARDIOLOGY DIVISION
(case manager 1)
HF Day Hospital
Strict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

IL PAZIENTE ED IL SUO VIAGGIO DA SOLO

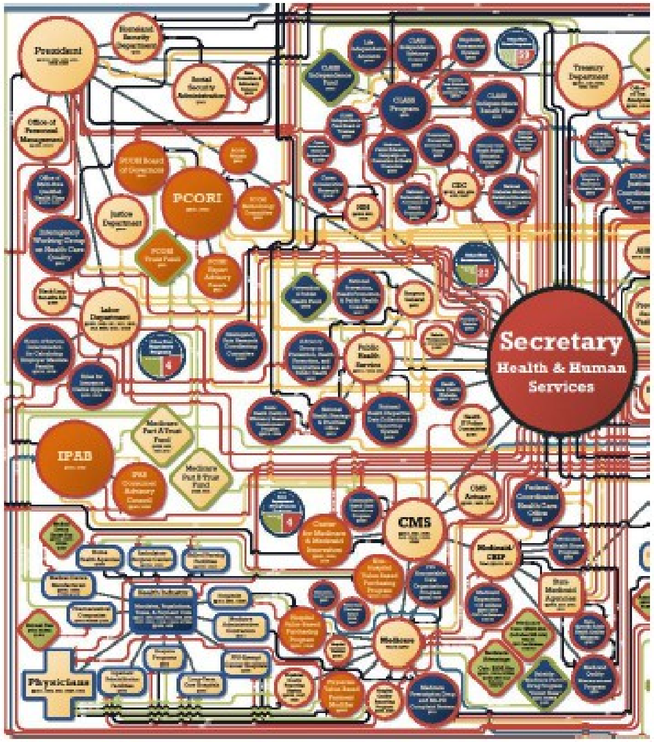

SOCIAL ENVIRONMENT
Social Networks
Built Environment
Pollution
Social Interactions
Culture, Governance, History, Social Organization
Knowledge
Technology, Health Services, Economics, Food Networks
Nature Interactions
Buildings, Residential and Occupational Structures
Transportation Systems
Public Greenspaces
Waste Management, Sanitation
Agriculture, Animal Husbandry
Ambient Air Pollutants
Water Pollutants
Land and Soil Contaminants
Noise and Light


NATURAL ENVIRONMENT
Geosphere
Biosphere
Location
Altitude, Latitude, Longitude
Climate
Sunlight, Temperature, Rainfall, Seasons
Geography
Land Features, Geology, Terrain
Pollutants
Volcanoes, Sand, Dust
Microbes
Plants
Animals
Forest Fires, Biogenic Emissions


PERSONAL ENVIRONMENT
Income
Wealth
Education
Occupation
Physical Activity
Sleep
Housing
Family Structure/ Acquaintances
Nutrition
Chemical Uses
Hierarchy, Power Structure, Occupational Exposure
Type, Location, Quality, Indoor Pollutants, Gardens, Indoor Plants, Pets, Domestic Animals
Tobacco, Alcohol, Recreational Drugs, Pharmaceuticals

Patient Journey: un percorso sequenziale

Per la costruzione del **Patient Journey si utilizzano le tecniche della mappatura di processo** per capire e «tracciare» l'esperienza del paziente attraverso l'identificazione degli eventi, dei passaggi e delle decisioni che avvengo durante tutto il percorso di cura.



La serie sequenziale dei passaggi nel provvedere alla cura del paziente può contenere **sia passaggi clinici che non clinici.**

Ad ogni step del percorso, il patient journey riflette le decisioni prese sia dai pazienti che dalle equipe di cura, il razionale dietro le decisioni e le emozioni provate.