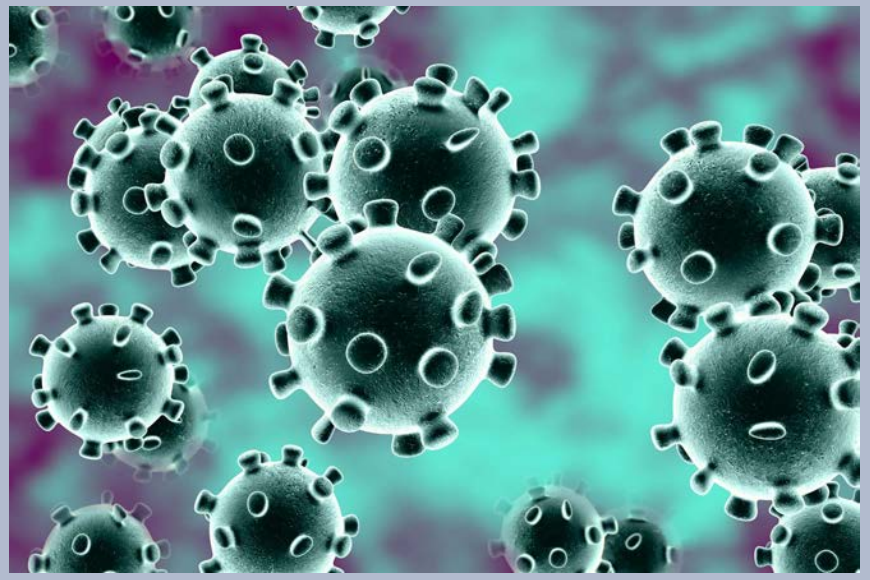
Data from wearables and patient entered data



in a time of Covid

PAIDUR: how to use mHealth in healthcare

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GP Paisley retd.

Short glossary for mHealth

mHealth	technological systems using mobile device(s) connected for healthcare
mHealth device	mobile device that is wearable or uses sensors for mHealth
mobile	a device that is self-powered and portable by one person
wearable	a mobile device fixed to the body and connected by Personal Area Network
point-of-care	acquisition of data in real time from a person or their samples
precision	uncertainty of data due to random factors
accuracy	uncertainty of data due to systematic factors

Assessment of physiological signs associated with COVID-19 measured using wearable devices | npj Digital Medicine (nature.com)

Natarajan, Su, and Heneghan Aug 2020 (ref 1)

FitBit® data: new signs?

- Resp Rate during deep sleep
- Heart Rate during non-REM sleep
- HR Variability = R-R Interval
- RRi entropy
- Onset of signs up to 5d before symptoms

	Prevalence % of 22 symptoms 2745 users of App	Hospitalisation Risk Predictor
Fatigue	72	
Headache	65	
Body ache	63	
Cough	59	10
Decrease in taste & smell	60	
Fever	55	4
Chills	53	
Shortness of breath	46	1
Congestion	46	
Loss of appetite	44	5
Chest pain	40	9
Diarrhoea	39	
Sore throat	38	
Neck pain	22	
Eye pain	19	
Hoarse voice	19	
Stomach ache	18	
Confusion	16	3
Vomiting	10	2
Rash	8	
Swelling In fingers & toes	5	7
Age		6
BMI		8

Do clinicians want new data? …

Issue	**Response**
More information to learn about?	yes … it's new
More technology to use?	by users, not by HCW
Data overload?	processing automatic, asynchronous few data items to add to the usual
So more work?	no

- devices or users do the data collection
- device processing independent of user or HCW
- data reuse can be automated on new platforms
- better diagnosis …

… and for what purpose?
6 healthcare scenarios for new data in Covid19

A	c**A**se-finding	in whole population
B	vulnera**B**le / at risk	pop^{n} selected for co-morbidity e.g. Care Homes
C	**C**ontacts	self-identified, contact-traced
D	**D**iagnosed cases	current: classic symptoms, other features, tests
E	r**E**covering cases	at home, or returned from hospital, managed by Primary Care teams, or Secondary Care (Hospital-at-Home)
F	**F**ailing to recover	chronic / long covid /at risk of relapse

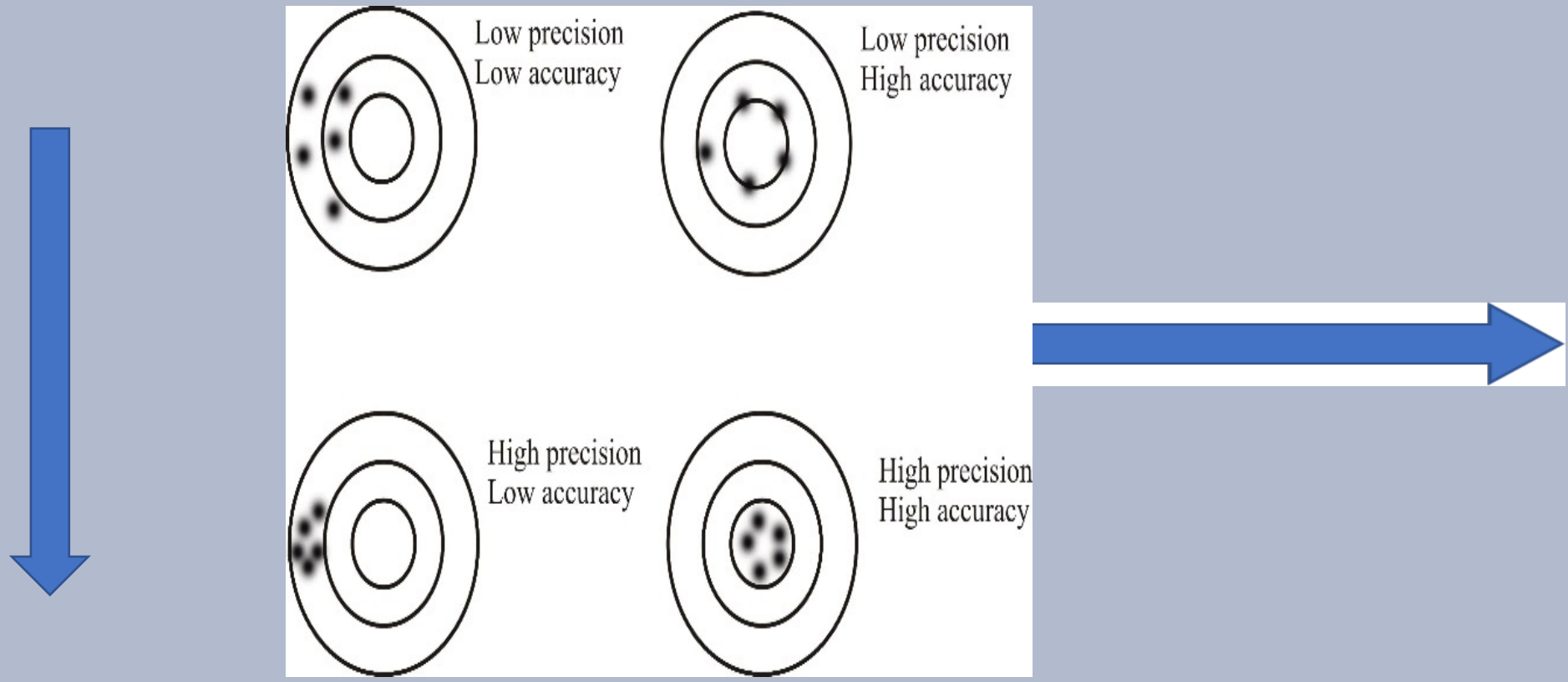
Data Quality

Precision

low random error

Accuracy

low systematic error



Data Quality

Precision

low random error

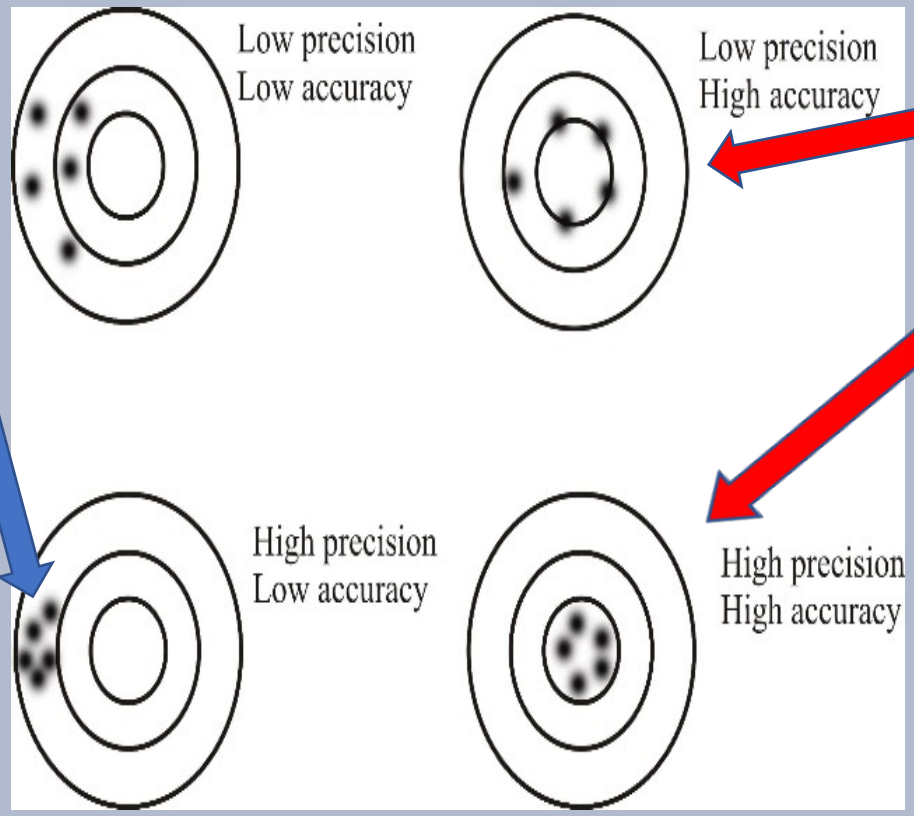
Coherence

Resolution(device)

No of digits (data) (significant)

Multiple data:
Test/re-test
Inter-rater

→ *internal consistency*



Data can be precisely wrong

Accuracy

low systematic error

weight, symptom scales

haem, biochem

Offset or bias:
trueness, linearity
SpO2 and skin tone (ref 3)

Validity types: selection, face, construct, content, criterion

Standardised
→ *external consistency*

Data Quality

Precision

low random error

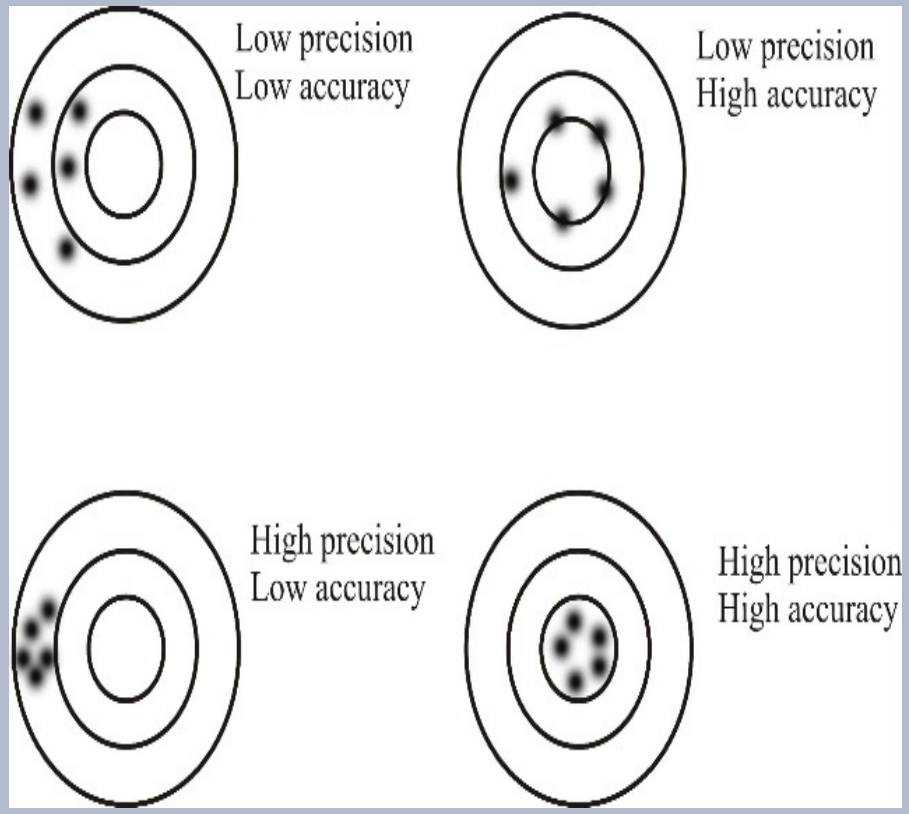
Accuracy

low systematic error

Is it any good?

For healthcare:

Is it good enough?



Is it any use?

Is the meaning for healthcare clear?

What is semantic validity?

Trueness? *quantitative*

Truth for *qualitative* data?

Let's use "**Veracity**"

His Master's Voice

"Nipper" by Francis Barraud 1898
™ The Victor Talking Machine Co.

Precision? No

Accuracy? No-but-Yes

This device delivers not only

Meaning

and

Veracity

but also

Asynchronicity

so

Records rare events

How devices have developed

	was ad-hoc	now solid-state, continuous, analogue
1. Temperature	Hg thread, thermocouple	thermal sensor
2. Blood pressure	Hg column + stethoscope	motion
3. Heart rate (HR)	manual	motion
4. Oxygen (SpO_2)	arterial sample	optical (PPG), skin (arterial)
5. Glucose	colorimetric	biochemical

Now

- all sensors' analogue data are ***digitised*** by ADC, ***processed*** by DSP etc
- ***data volume reduced*** by ***on-device processing***, from Mbit to bit (single)
- ***co-processing*** of multiple data types
- ***classifies*** native data, to reduce data, add ***meaning*** → display with interpretation
- ***automatic*** so ***continuous*** 24/7 data collection, so ***asynchronous*** with ***no missing data***

Microwear L8
£25

SoC Nordic® nRF52832

Maxwatch
£20

Realtek® RTL8762C

MiBand 6
£35

Dialog® DA1469x

Dialog® DA1469x System-on-Chip

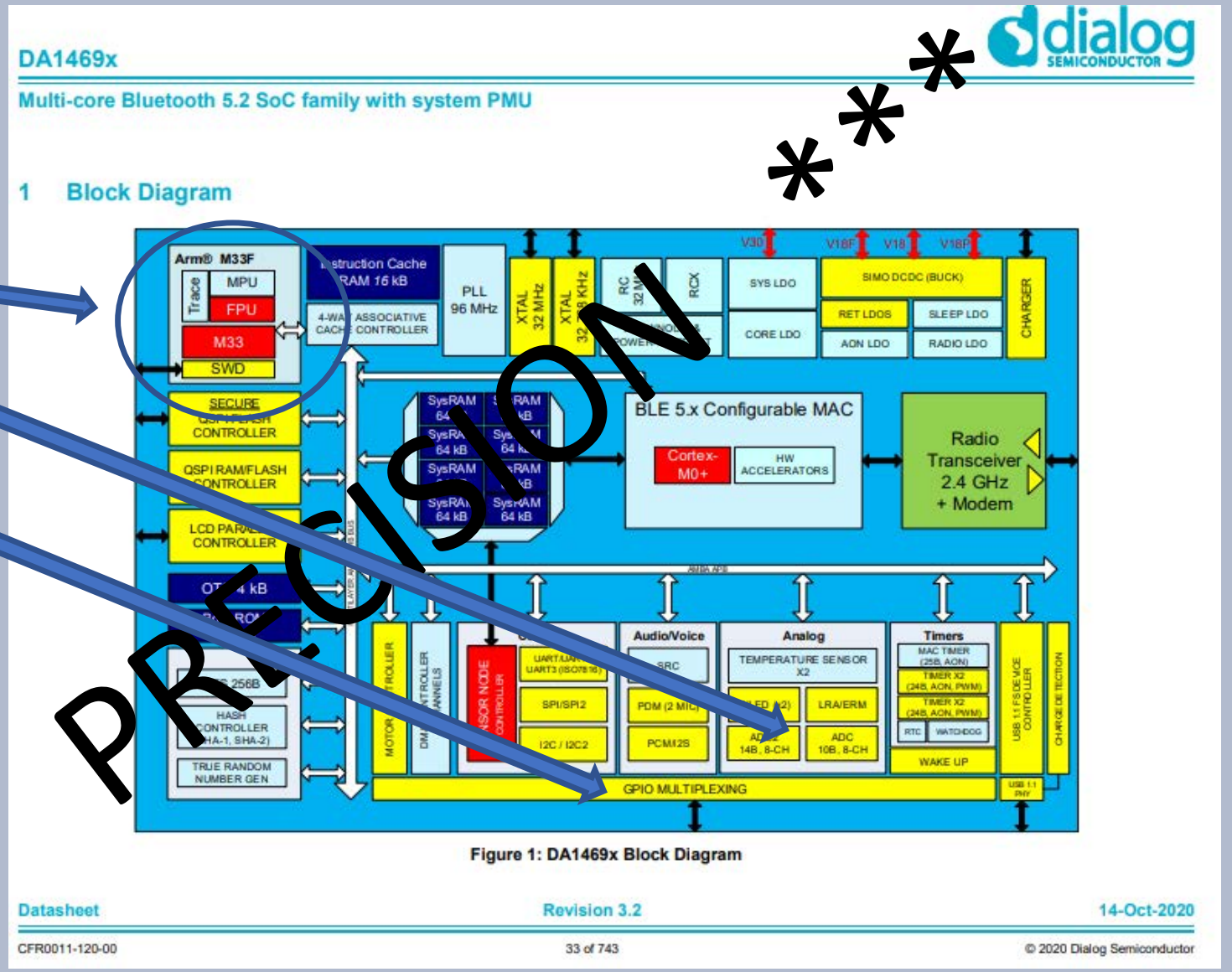
ARM Cortex® CPU

14- and 10-bit ADCs

55 x I/O interfaces for analogue sensors

Published SDK

https://github.com/dialog-semiconductor/BLE_SDK10_examples#readme



PRECISION

https://www.mouser.co.uk/new/dialog-semiconductor/dialog-da1469x/

Precision = min. random errors

Engineering of device = whole system

incl. stable fix to skin? same issue if £20 or £400

Wearable e.g. on wrist - tho worst location

- multi-day wear, PAN connect via BT

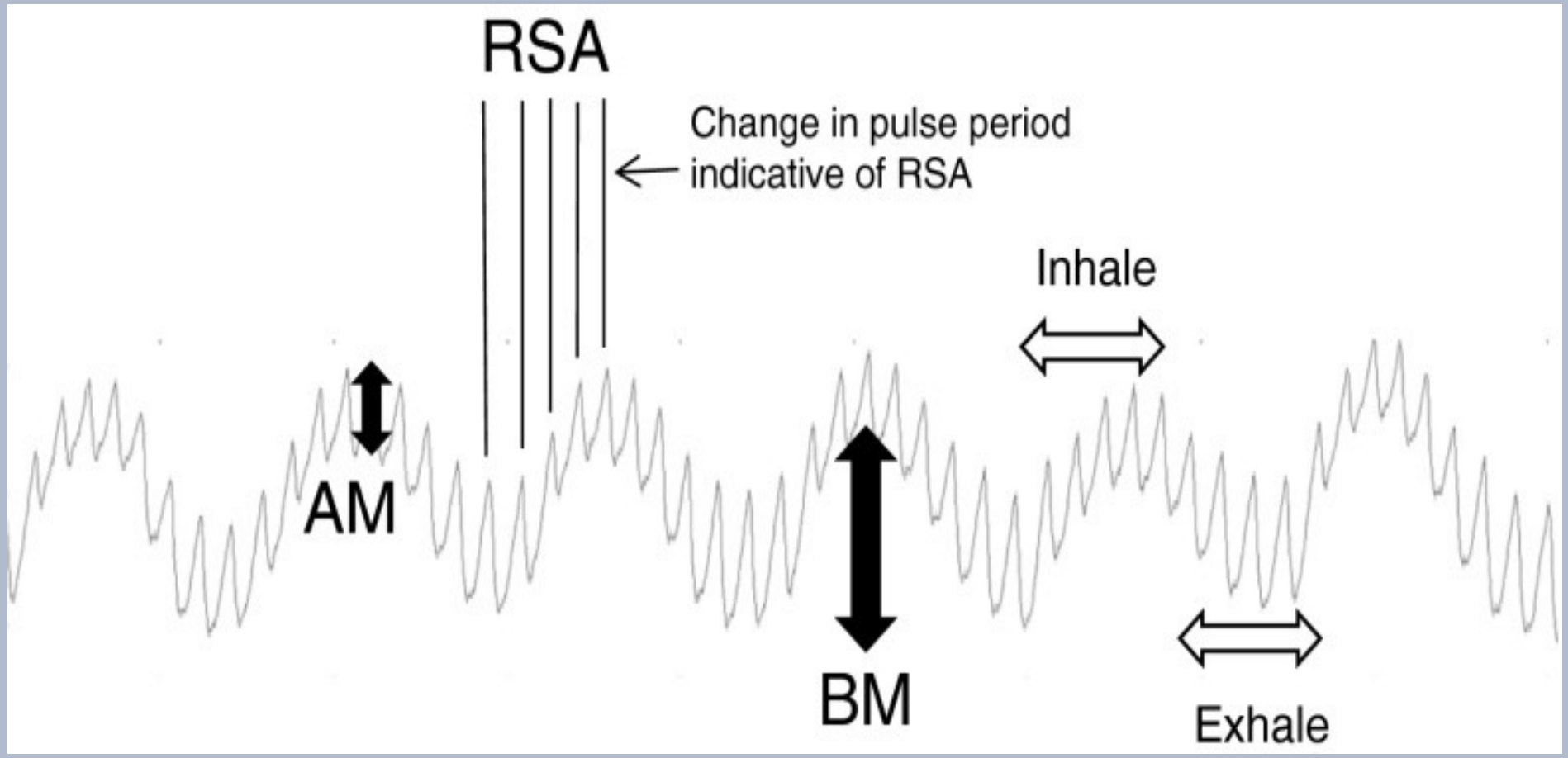
Freestyle Libre fixing system

- needle sensor + adhesive, replace every 14d.
- PAN connect via NFC, else BT
- for scenarios D and F?

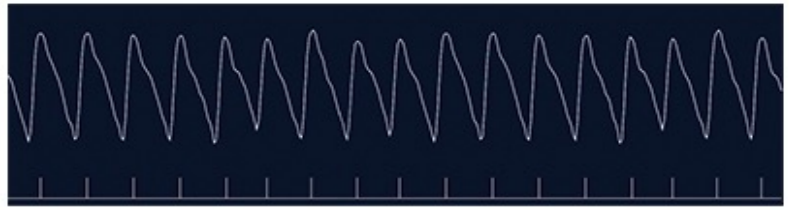
Precision: test-retest improved by fix duration

- repeat / replicate / reproduce

Derivatives: Resp. Rate from PPG Pulse wavelet (ref 4)

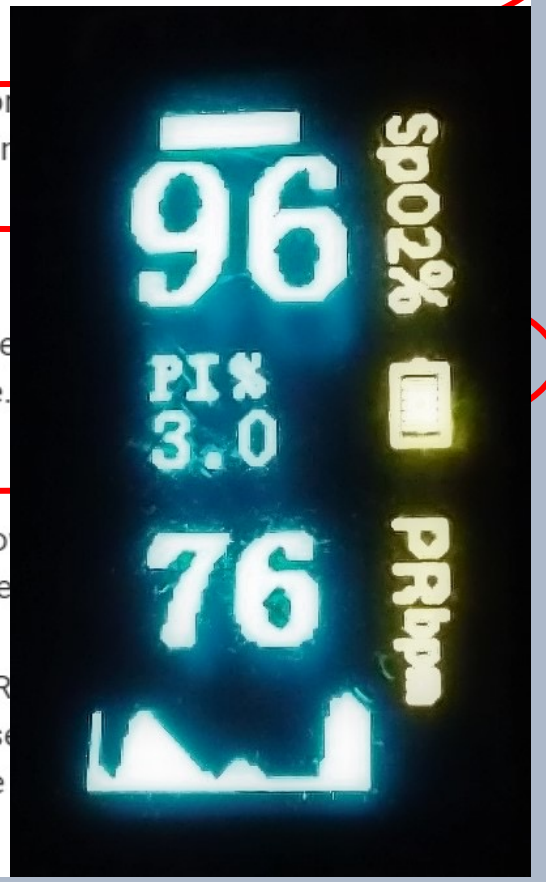


Masimo™ MightySat Rx® Fingertip Pulse Oximeter



High-resolution view of the pleth waveform when viewed on a smart device.

- Signal IQ® (SIQ)
  Located under the plethysmographic waveform. The height of the vertical line provides an assessment of the confidence in the SpO_2 value displayed.
- Plethysmographic (Pleth) Wavefor
  Real-time graphical representation
  arterial blood with each pulse.
- Perfusion Index (Pi)
  A measure of the dynamic change
  occur during the respiratory cycle.
- Pleth Variability Index (PVi)
  The ratio of the pulsatile blood flo
  peripheral tissue used to measure
- Respiration Rate from the Pleth (R
  A measure of respiration rate base
  plethysmographic waveform. The
  per minute (RPM).



https://www.masimo.com/products/monitors/spot-check/mightysatrx/

Devices co-process new data from multiple sensors

Photoplethysmography “PPG”
for HR, HR variability, respiratory rate, SpO_2

Accelerometers, gyroscopes
for Activity

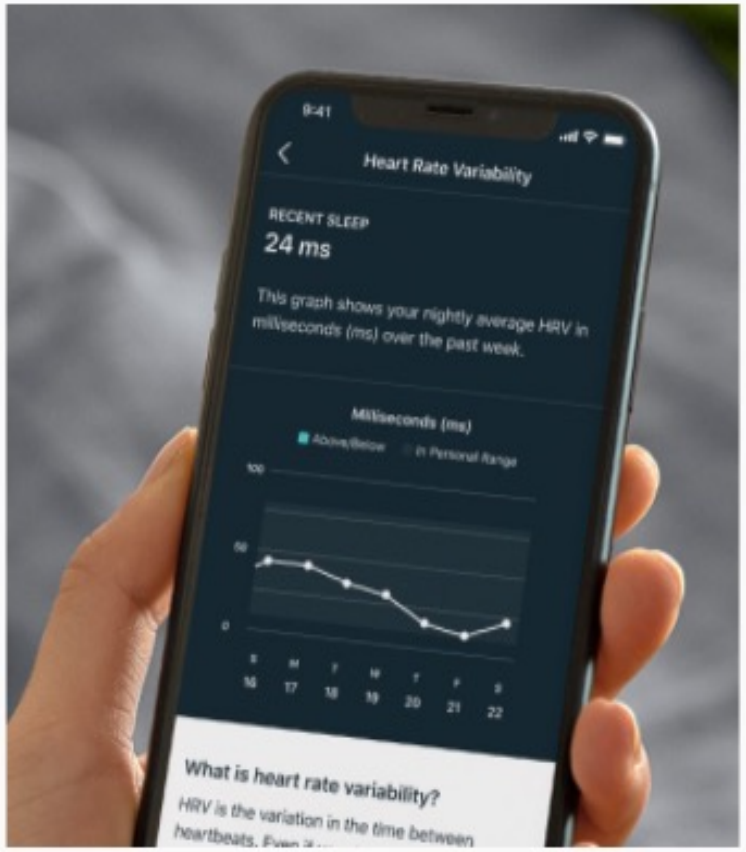
- workouts → Personal Activity Intelligence
- inactivity → frailty
  → falls risk

pulse, inactivity, resp. rate, HRV, temp, time
for Sleep

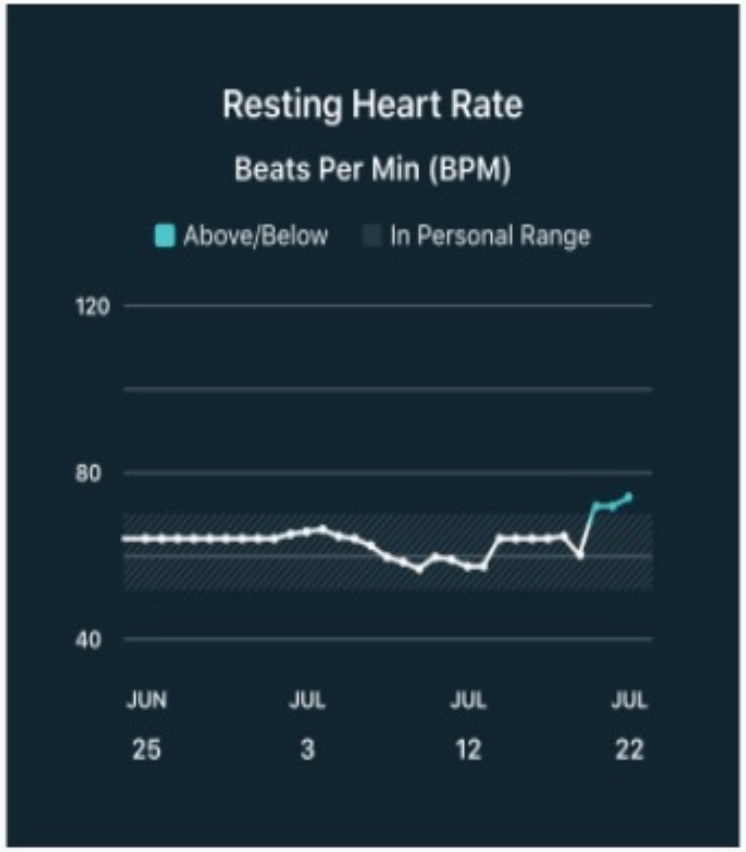
- Duration, quality - 3 phases

Consumer features: usability, battery life/charging
On-device advice, help → meaning → trust

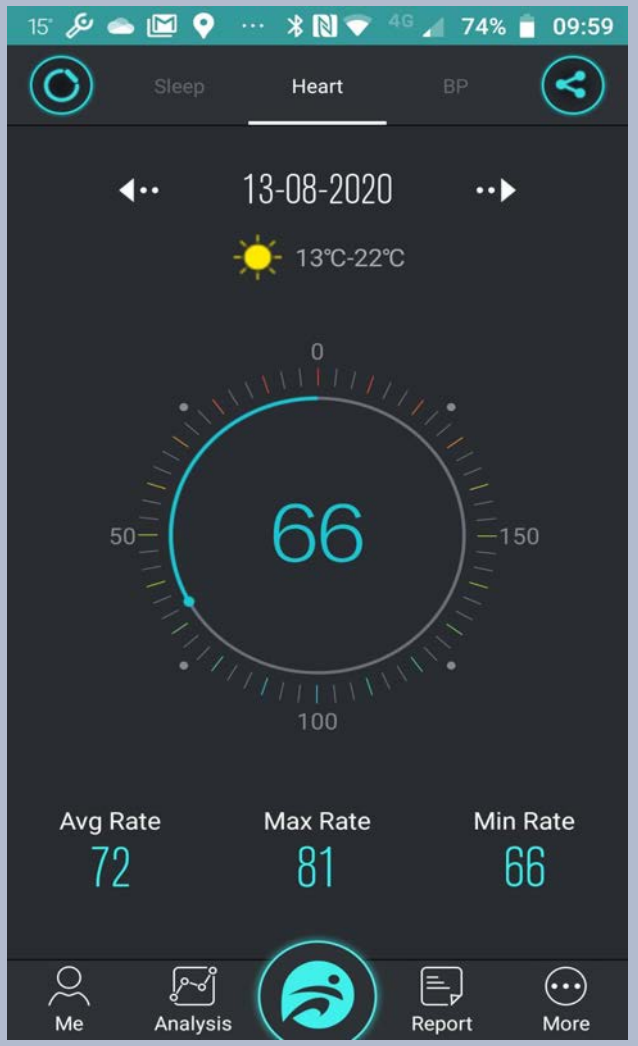
Apps to interpret for us



Heart Rate Variability



Resting Heart Rate



⇑ FitBit® apps ⇑ and many others e.g. Fundo® app ⇑

How to acquire *"Everyday Data"*®? Automate!

Deploy	purchase, supply, install
Initialise	phone/wearable with phone connectivity via PAN by BLE, ANT, NFC • fix for stability and comfort esp. PPG devices
Operate:	UX and UI • decouple data collection from minimised user actions • timing: scheduled batch intervals, or stream • max. on-device processing for min. user action
Maintain	reliability, power management, repair/replace

Everyday automation is 24/7, so

- asynchronous
- collects baseline and negative data that a human user would ignore
- detects rare events

Hospital-at-Home schemes

NHS Scotland

- “Home and Mobile Health Monitoring” now “Connect Me”
- services for: Local Covid19, COPD, BP, CHF …
- based on Inhealthcare® platform
- prompts patients x2/d by app, SMS text or phone, to report symptoms and data, and may automatically warn to seek help via 111 or 999
- devices: BP, scales, oximeter (SpO2/HeartRate/RespRate) therm, PFR meter, symptoms
- licence, ownership issues

Real-time remote monitoring platform by HAS™ now Technicare™

Accelerometer, HR data per Polar® devices

Inactivity >5mins sends alert
If still inactive, sets tag for algorithm.
(Inactivity tags have Veracity)

“ARMED uses a range of wearable technologies to identify those who may be at risk of falling, and as a minimum, Polar® devices are required … (also) additional wearables … activity & sleep trackers, grip strength measurers, body composition scales, heart rate variability sensors, environmental sensors (etc).“

https://www.technicaresolutions.co.uk/solutions

ARMED (Advanced Risk Modelling for Early Detection) – UK Gov Digital Marketplace

What is RHR?

What it's not:

Minimum HR over 24hr (= 05.00)

Basal HR (= daytime)

Point HR
at set # beats after set exercise
after 12min. of zero steps

Min HR over 5min. after 10min rest

Such definitions give 35% inter-"device" uncertainty

1. What's resting heart rate (RHR)?

According to the American Heart Association's defini-tion, RHR is the number of heart beats per minute when a person is awake and not moving. A normal person has an average RHR of about 55-79 beats/min. It is an im-portant measure of a person's cardiopulmonary health. People who exercise a lot and professional athletes are usually in a better myocardial condition, and their RHR is usually lower.

2. How do smart devices measure my RHR?

The RHR must be measured when the body is relaxed. The device uses your heart rate when you are asleep as its basic data, and then estimates your RHR by using a scientific algo-rithm. To ensure a normal measurement of your RHR, please wear the smart device when you go to sleep.

Resting Heart Rate Covid19 DETECT a new sign?

How can my activity tracker or wearable device help?

- Recent research has shown that when people get an infection there can be changes in the rate of their heartbeat, as well as daily sleep and activity patterns as measured by the devices you might be using.
- By trending this information over time, we may be able to identify the start of an outbreak much earlier than waiting for people to show up at emergency rooms.

Which devices can I connect to the DETECT study?

- You can connect your smartphone and your connected wearable smartwatch or activity tracker.
- These include *devices such as Fitbit, Apple Watch, Garmin, Withings, Amazfit, Oura, Beddit or*

Anything that can share data with

- Google Fit (if Android phone) or
- Apple HealthKit (if iPhone)

https://detectstudy.org/

(ref 6)
18.11.20

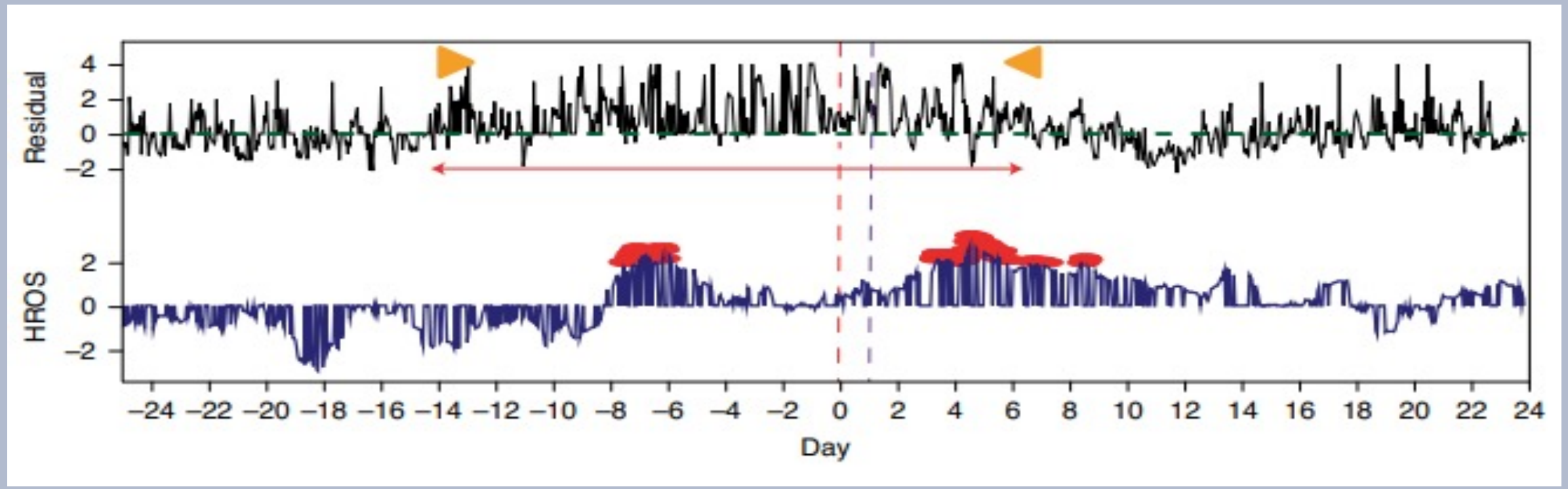
- 26/32 had alterations in their **heart rate**, no. of daily **steps** or time **asleep**.
- 22 detected before (or at) symptom onset, 4 cases ≥ 9d earlier
- 63% of the COVID-19 cases could have been detected before symptom onset **in real time** via a two-tiered warning system based on the occurrence of extreme elevations in **Resting Heart Rate relative to the individual baseline**
- **New feature: Heart Rate Over Steps (HROS)**
  by dividing heart rate by steps
- **AnomalyDetect** algorithm can be used with either RHR (Resting Heart Rate) or HROS (Heart Rate Over Steps)
- This works for any smartwatch data "like FitBit, Apple, Garmin and Empatica"

See https://github.com/gireeshkbogu/AnomalyDetect

ARTICLES
https://doi.org/10.1038/s41551-020-00640-6
nature biomedical engineering
Check for updates

Pre-symptomatic detection of COVID-19 from smartwatch data

(ref 6)
18.11.20



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Science Blog (corona-datenspende.de)

Heart Rate and Activity data measured by the wearable devices and smart watches of more than 520,000 “data donors”

Data Donation app supports devices from

- Amazfit, Fitbit, Garmin, Huawei, Oura, Polar, Withings; or if connected by Google Fit
- Apple Health, Samsung now dropped

We calculate the donor’s baseline … using data from their entire time window

Processing in RKI Cloud normalises for local climate: temperature, cloudiness, rainfall

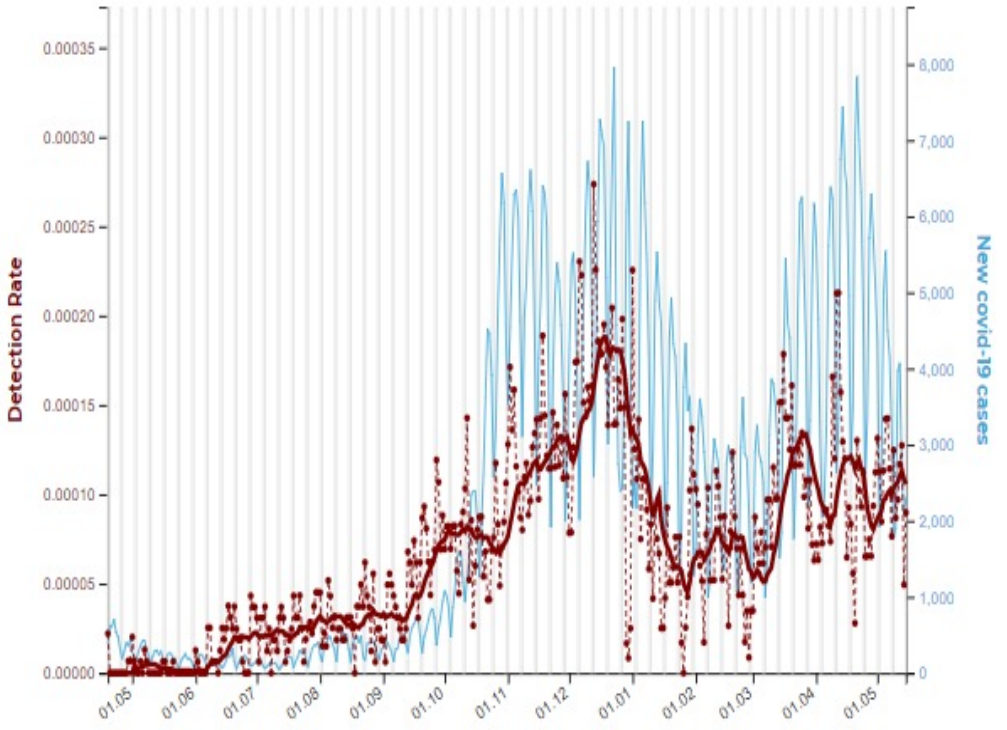
Note “fever” is not actual temperature, but a derivative of RHR and activity, normalised a/a

“Your personal health data is associated with the pseudonym. We ask you to keep it secret for security reasons like an ordinary password.”

Current Fever Curve for Germany

The curves in the figure below depict positive fever detections in the group of data donors as a function of time. The estimated number of positive detections is computed from the donated data and updated daily. These results are part of the core purpose of the Corona Data Donation Project.

Fever detections based on resting heart rate and daily step count



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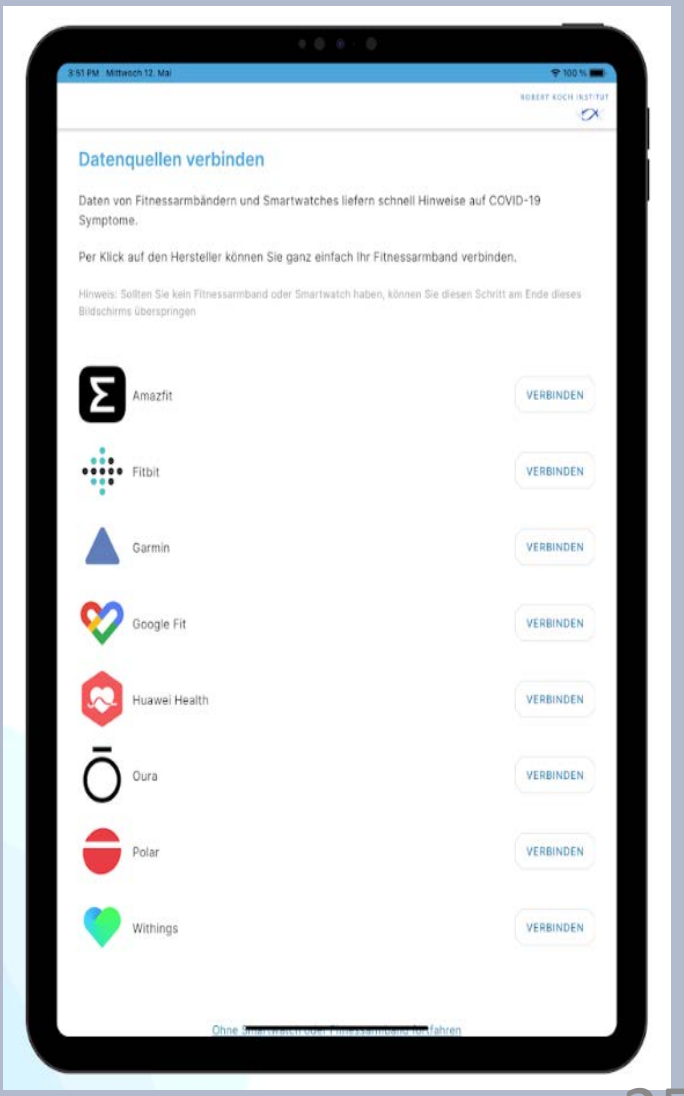
HR, steps and sleep data

Corona-Datenspende – Apps

	Fitbit	Garmin	Polar	Withings	Google Fit	Apple Health	Samsung Health	Oura	Amazfit
Activity	✓	✓	✓	✓	✓			✓	✓
Activity detail (running, cycling, sports etc.)	✓	✓	✓	✓	✓				✓
Quiet	✓	✓	✓					✓	
Steps	✓	✓	✓	✓	✓	✓	✓	✓	✓
Calorie consumption	✓	✓	✓	✓				✓	✓
Covered track	✓	✓	✓	✓	✓			✓	✓
Climbed stairs	✓	✓		✓					
Sleep	✓	✓	✓	✓	✓	✓	✓	✓	✓
Vital signs									
Pulse	✓	✓	✓	✓	✓	✓	✓	✓	✓
Body temperature			✓	✓					



Heart Rate over Steps: a new sign?

Precision

- user-device pairing
- serialisation per user
- technology factors

Good enough

Accuracy

- veracity for healthcare is good
- standard ROC metrics
  - RHR alone
    - AUC 0.5, sensitivity 39%, specificity 80%
  - RHR + sleep + steps + symptoms
    - AUC 0.8, sensitivity 72%, specificity 73%

How could we use HROS?

as we do with other data: co-process

- clinical context
- sensitivity ~40% cf. temperature

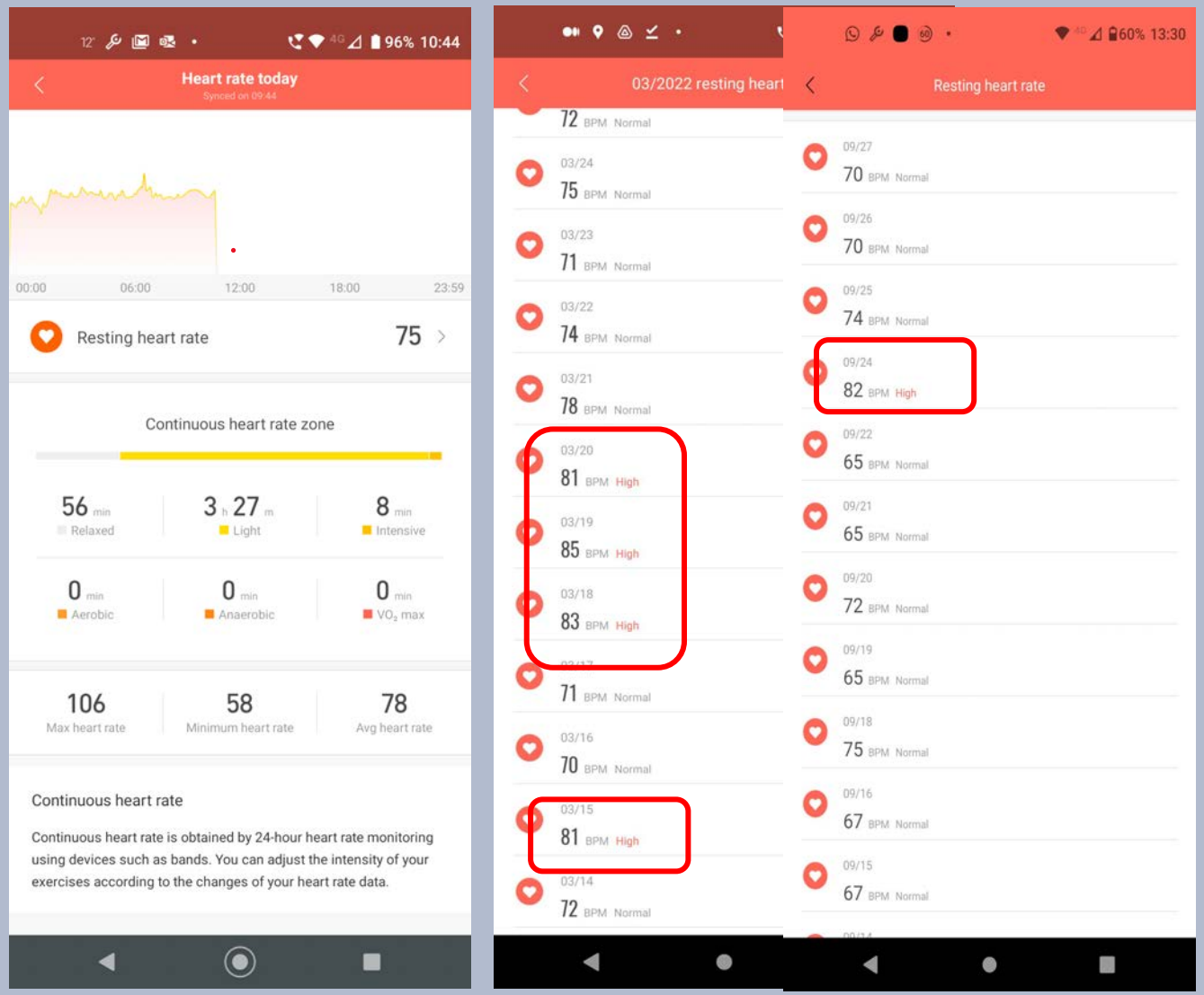
... temperature screening to detect COVID-19 ... | BMC Public Health

- "index of suspicion" (qualitative)
- Risk Predictor Tools (quantitative)

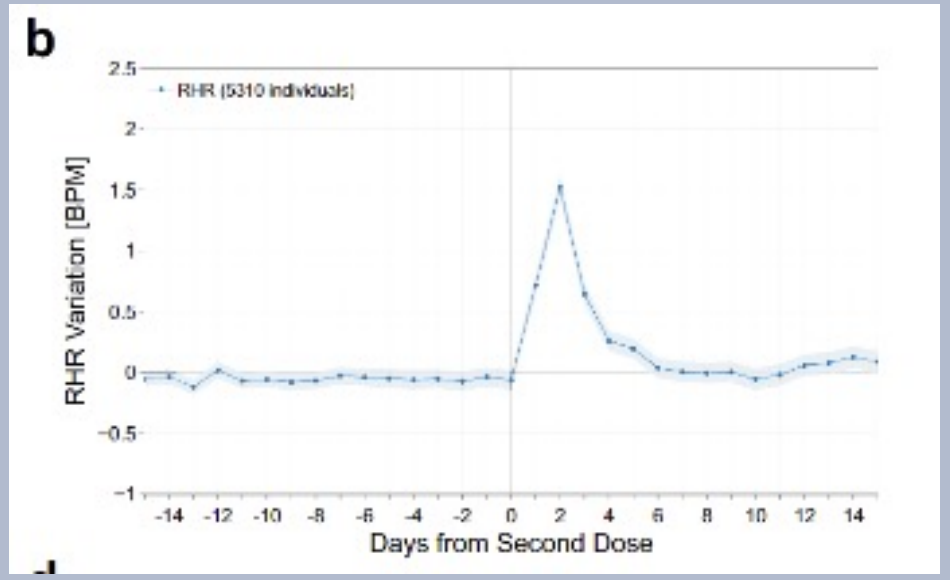
COVID-19 Clinical Risk Assessment Tool ... RECAP risk prediction tool ... Lancet DH

Wearable sensor data and self-reported symptoms for COVID-19 detection Nature Medicine https://www.nature.com/articles/s41591-020-1123-x

The veracity of RHR



[Inter-individual variation … following COVID-19 vaccination via smartwatches and fitness bands
npj Digital Medicine (nature.com)]



"Interindividual variation in RHR response to vaccines may correlate with individual immune response … wearables could offer a way to easily quantify someone's immune response to a vaccine and allow for changes in preventative strategies, such as giving an early booster shot"

Interoperation of multiple data formats

Google Fit	exports as TCX (used by Garmin and Strava) also CSV
Syncs with	Runkeeper, Strava, adidas Runtastic, Map My Fitness etc
Fitbit	exports as JSON and CSV
Syncs with	FitToFit app, or to Strava, else IFTTT
Apple Health	exports as XML and CSV
Syncs with	Map My Run, Strava, Fitbit to Apple Health Sync, Garmin
Strava	exports as CSV, imports as .GPX, .TCX, .FIT
Syncs with	www.strava.fitbit.com

Fitness Syncer and data formats

www.fitnesssyncer.com - supported apps and services

52 apps incl.	Apple Health / Fitbit / Garmin / GoogleFit MapMyFitness / Samsung / Strava / Suunto
6 data services	Amazon S3 / Dropbox / Google Drive / MS OneDrive / FitnessSyncer Notebook / email
12 data items	activity / nutrition / allergy / medications / condition / body composition / SpO_2 / BP / sleep / glu / temp / cholesterol

Non-proprietary?

GitHub - Bellafaire/ESP32-Smart-Watch

Open source smartwatch based on ESP32 compatible with the Arduino IDE.

PineTime | PINE64

A free and open source smartwatch capable of running custom-built open operating systems … includes a heart rate monitor …

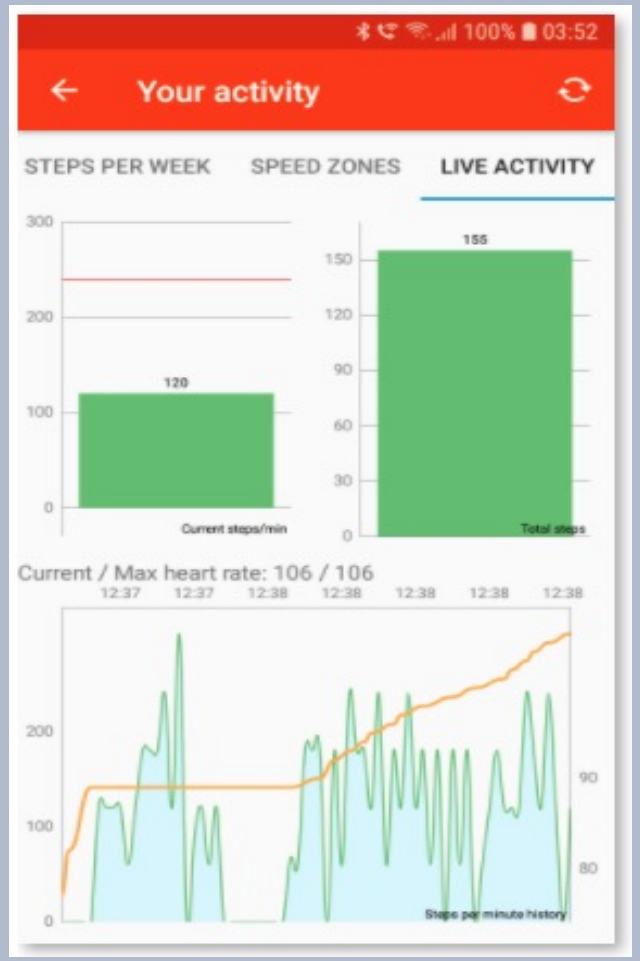
It is a fully community driven side-project.

Software: any open-source OS

SoC: Nordic Semiconductor nRF52832

Gadgetbridge

A free and cloudless replacement for your gadget vendors' closed source Android applications.



Feature Matrix

	Pebble OG	Pebble Time/2	Mi Band	Mi Band 2	Mi Band 3	Mi Band 4/5	Amazfit Bip	Amazfit Cor
Calls Notification	YES	YES	YES	YES	YES	YES	YES	YES
Reject Calls	YES	YES	NO	NO	YES	YES	YES	YES
Accept Calls	NO(2)	NO(2)	NO	NO	NO	NO	NO	NO
Generic Notification	YES	YES	YES	YES	YES	YES	YES	YES
Dismiss Notifications on Phone	YES	YES	NO	NO	NO	NO	NO	NO
Predefined Replies	YES	YES	NO	NO	NO	NO	NO	NO
Voice Replies	N/A	NO(3)	N/A	N/A	N/A	N/A	N/A	N/A
Calendar Sync	YES	YES	NO	NO	NO	NO	NO(3)	NO
Configure alarms from Gadgetbridge	NO	NO	YES	YES	YES	YES(1)	YES	YES
Smart alarms	NO(1)	YES	YES	NO	NO	NO	NO	NO
Weather	NO(1)	YES	NO	NO	YES	YES	YES	YES
Activity Tracking	NO(1)	YES	YES	YES	YES	YES	YES	YES
GPS tracks import	NO	NO	NO	NO	NO	NO	YES	NO
Sleep Tracking	NO(1)	YES	YES	YES	YES	YES	YES	YES
HR Tracking	N/A	YES	YES	YES	YES	YES	YES	YES
Realtime Activity Tracking	NO	NO	YES	YES	YES	YES	YES	YES
Music Control	YES	YES	NO	NO	NO	YES	NO	YES
Watchapp/face Installation	YES	YES	NO	NO	NO	YES	YES	YES
Firmware Installation	YES	YES	YES	YES	YES	YES	YES	YES
Taking Screenshots	YES	YES	NO	NO	NO	NO	NO	NO
Support Android Companion Apps	YES	YES	NO	NO	NO	NO	NO	NO

Device Trust:

HCW Trust in Devices

Which patient devices do you, as HCW, always trust to give valid data?

- digital thermometer
- oximeter
- digital weight
- digital BP
- glucose CGM
- weight scale
- fitness-tracker/smartwatch

Ranks familiar data with digital displays and new data from mHealth devices

Toys or Tools?

Device Features for HCW Trust

Which features support a HCW to trust an mHealth device ?

- regulatory certification
- published evaluations
- precision
- accuracy
- user competence
- brand name
- cost to user

Business Models: Trust Privacy - and £££

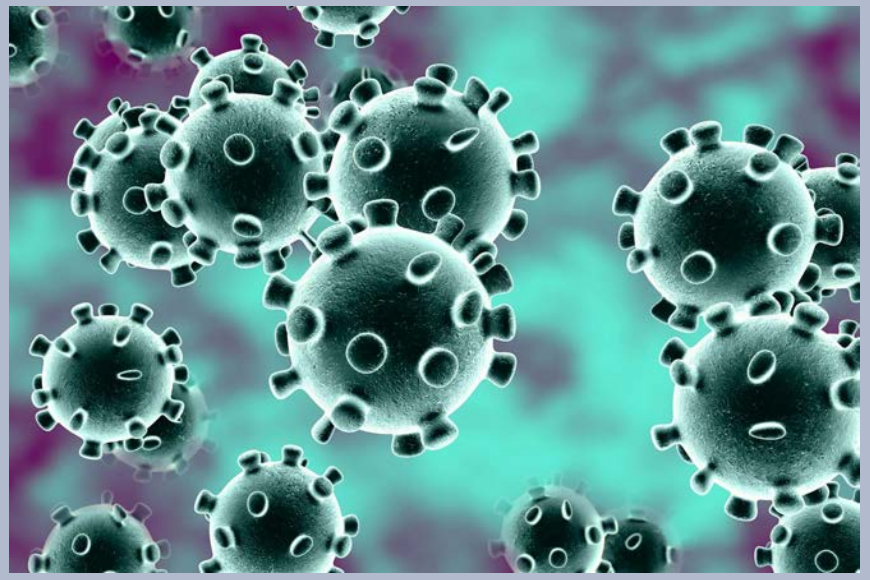
Free with user tracking	“The User is the Product”, “Privacy is History”
Freemium	core service is free-to-use, but limited +features are +cost automation? UI customisation? battery life? on-site replacement?
Subscription	user pays for selected features
Hybrid	can NHS use core data in a FOC service and make it universal?

Without Trust there’s no consent to reuse anything

PAIDUR: a framework for mHealth in healthcare

Precision	engineering design	↔	quality of manufacture
	resolution	→	error metadata
	user-device pairing	→	serialisation
Accuracy	standardised	→	veracity
Interoperation	numeric data	→	error metadata
	standard data models	↔	API/direct access
Deployment	trust by user and HCW	↔	price
	connectivity phone, internet	↔	initialisation
Usability	automation/HCW assist	↔	UI,UX
	power management		wearable/fixable
	reliability	→	maintenance/re-supply
	24/7 data collect, process	→	rare event capture
Reuse	user control across systems core data for NHS / premium data for business trust required for any reuse.		

Data from wearables and patient entered data



in a time of Covid

PAIDUR: using mHealth in healthcare

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GP Paisley retd.

References

see also citation URLs on slides

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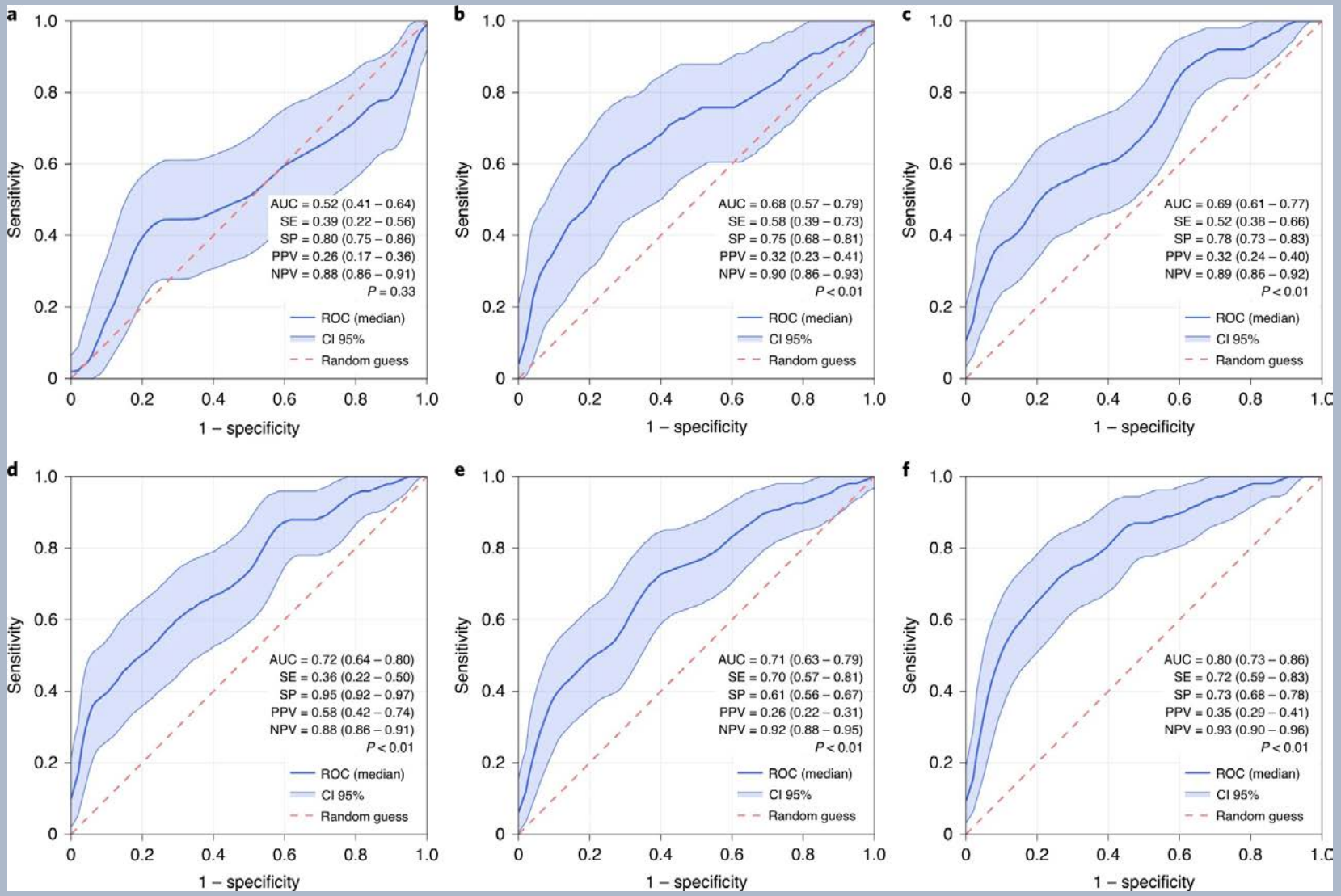
Prediction of COVID-19 from self-reported symptoms and sensor data

Fig. 2: Prediction of COVID-19 from self-reported symptoms and sensor data. | Nature Medicine



a–f, Receiver operating characteristic curves (ROCs) for the discrimination between COVID-19-positive (54 individuals) and COVID-19-negative (279 individuals) cases based on the available data: RHR data (a); sleep data (b); activity data (c); all available sensor data (d); symptoms only (e); symptoms with sensor data (f).

Why do we need more data?
To predict risk for complex conditions by calculation - not by mental arithmetic

Frailty

A syndrome of many datapoints

Cumulative Deficit model :

Clegg's eFrailty Index is compiled from up to 36 data items routinely held in health and care

Direct Healthcare utility unclear

Covid19

A difficult diagnosis in 2 parts

Clinical

- Cough, fever, smell changes, headache etc.

But 17 more are non-specific in elderly

- Fatigue is most prevalent symptom
- 6 phenotypes/syndromes known in adults

Lab tests

- Antigen tests not precise for infection risk
- Antibody tests not accurate for immunity

Frailty Indices are NOT reliable for calculating Predictions of Risk for Covid19

Qualitative, quantitative and pseudo-quantitative data

So much healthcare data is not quantifiable or computable:

Clegg's eFrailty Index: a simple sum of binary values (presence/absence of deficits) variably derived from a mixture of datatypes.

Mapping eFI to Rockwood's Clinical Frailty Scale (ref 2):

Table 3: discrete classes from continuous eFI data

Rockwood CFS name (9 classes as text:)	V fit, well, managing, vulnerable	Mild	Moderate	Severe	V severe, terminal
Clegg eFI scores	<12	12-23	24-35	>36	-

9 CFS classes reduced to 4 "fit / mild / moderate / severe frailty" as quartiles
eFI resolution reduced from 36 to 4, to enable use of 2 codes.

Precision	binary data; sub-classifications (polypharmacy ≥ 5) serial scoring per user improves precision
Accuracy	what is Veracity of eFI cf. component data? Moderate and Severe classes → Actions per GMS Contract.

Advanced Risk Modelling for Early Detection "ARMED"©
A real-time remote monitoring platform by HAS™ now Technicare™

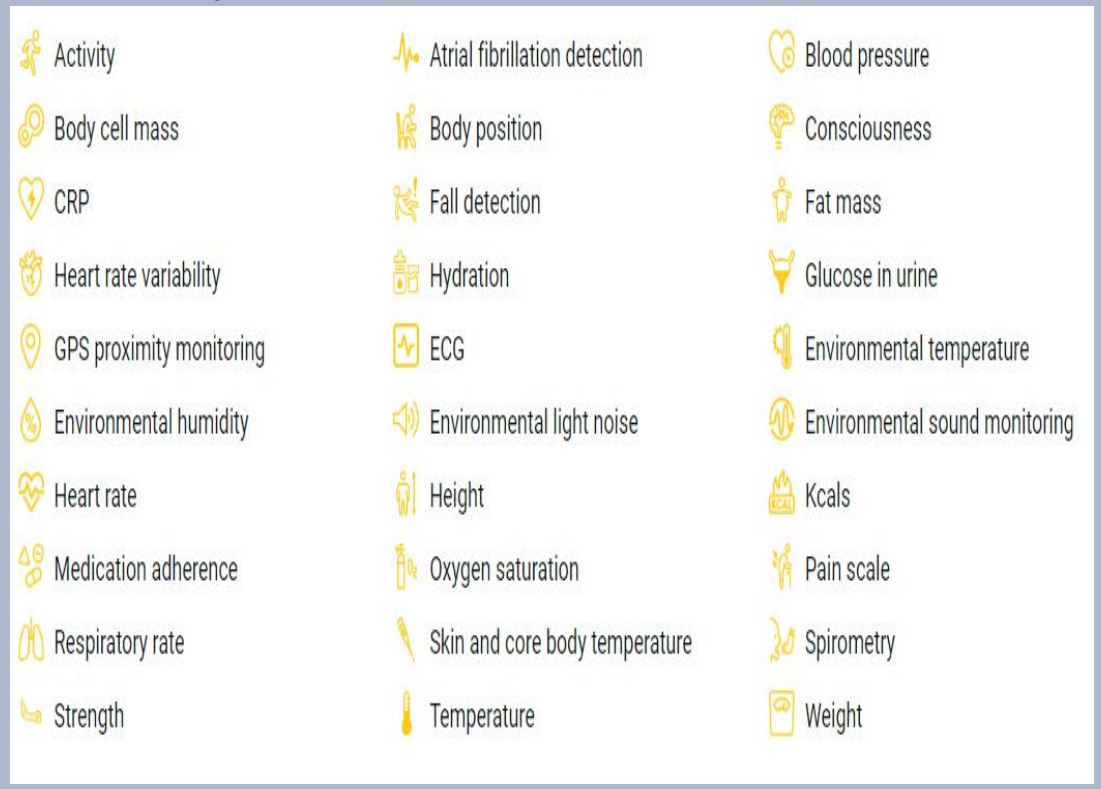
Accelerometer, HR data per Polar® devices

Inactivity >5mins sends alert
If still inactive, sets tag for algorithm.

Inactivity tags have Veracity

"ARMED uses a range of wearable technologies to identify those who may be at risk of falling, and as a minimum, Polar devices are required … can be complemented by additional wearables, such as activity & sleep trackers, grip strength measurers, body composition scales, heart rate variability sensors, environmental sensors (etc)."

Over 30 parameters now monitored:



https://www.technicaresolutions.co.uk/solutions

ARMED (Advanced Risk Modelling for Early Detection) – UK Gov Digital Marketplace

4 Research Questions

1. What are the types of data usable in Risk Predictors?
2. Which types of data can be Extended using new informatics resources?
3. How can Extended Data be Automated as Everyday Data?
4. How to render Everyday Data for generic use in any Health and Care system?

IG issues

1. Devices supplied by user
2. Software installed by user with acceptance of licence terms

However, when One-device is for One-user

1 User-supplied personal device acquires trust by successful use — Precision

2 auto calibrates to the norm for that combination - — Accuracy

Data is offered to HCW for consideration for use as NHS data = “history”

- This professional consideration includes context or provenance
- Provenance can be explicit, and integrated as metadata

2 Health data often acquired by traditional technology e.g.

- User supplies data from Home BP machines, thermometers, weight, oximeter
- Grip Strength meter is operated by the user, data transcribed by user or HCW

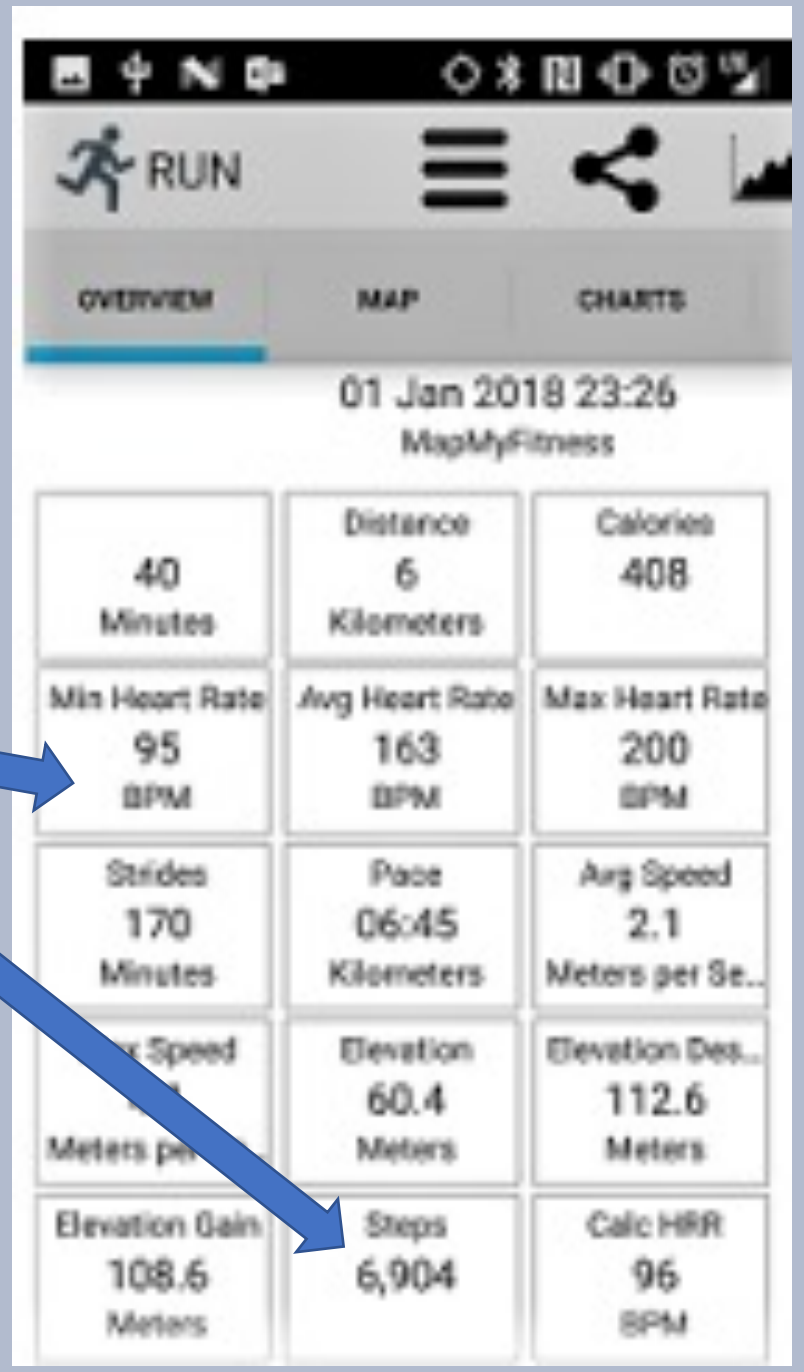
Trans-forming data #1

Fitness Syncer dataset:

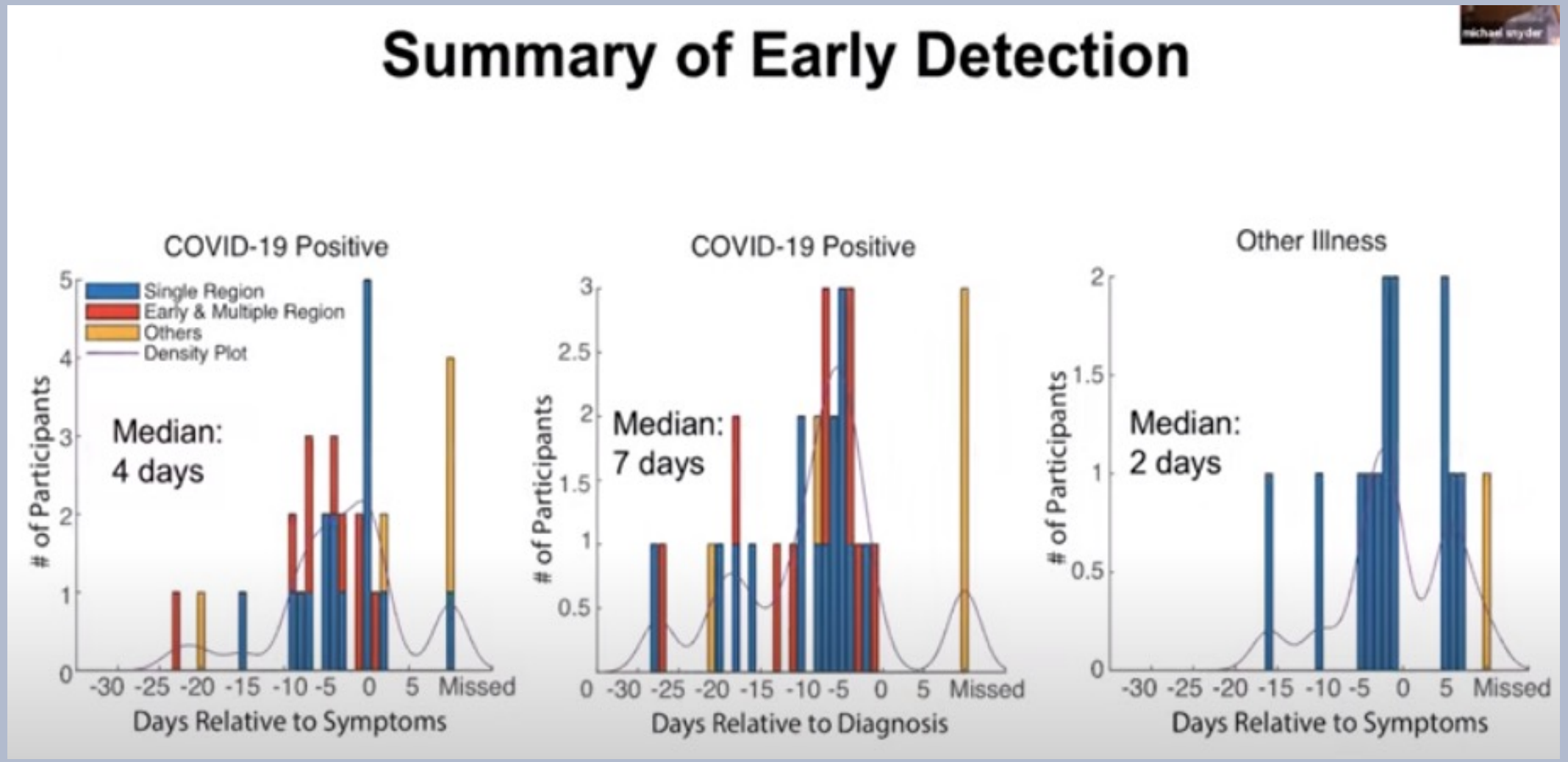
6 classic
5 new
Everyday items*

	generic	format	unit	comment
(In)activity*	y	Num	Event/hr	
Nutrition	y	a/n	Code	
Allergy	y	a/n	Code	
Medicatn	y	a/n	text	Text only
Body Comp^{n}	Y	Num	%	
Body Comp^{n} 2	y/n	Num	kg/m^2	
SpO2*	y	Num	%	
Condition	y	a/n	Code	
BP*	y	Num	mmHg	
Sleep*	y	a/n	Code	
Glu	y	Num	Mmol/l	
Temp*	y	Num	^{o}C	

Fitness Sync shows
Min. Heart Rate and
Steps



Wearables and Early Detection of COVID-19 Using a Smartwatch - DOM Grand Rounds - 30 Sept 2020 Dr Michael Snyder Stanford Uni



Beverley Bryant

Chief Digital Officer

Guy's St Thomas' &

Kings College Hospital NHS FTs

UK Faculty of Clinical Informatics

Virtual Scientific Conference #1

Thursday 8.10.2020

"Sometimes we have to show clinicians what is possible"

Cogstack Canary

Analyses freetext for keywords

e.g. cough, fever,

and normalises e.g. by excluding negations

Precision

Device Precision – confidence in
How often do you recheck with your own device data from a patient's device?

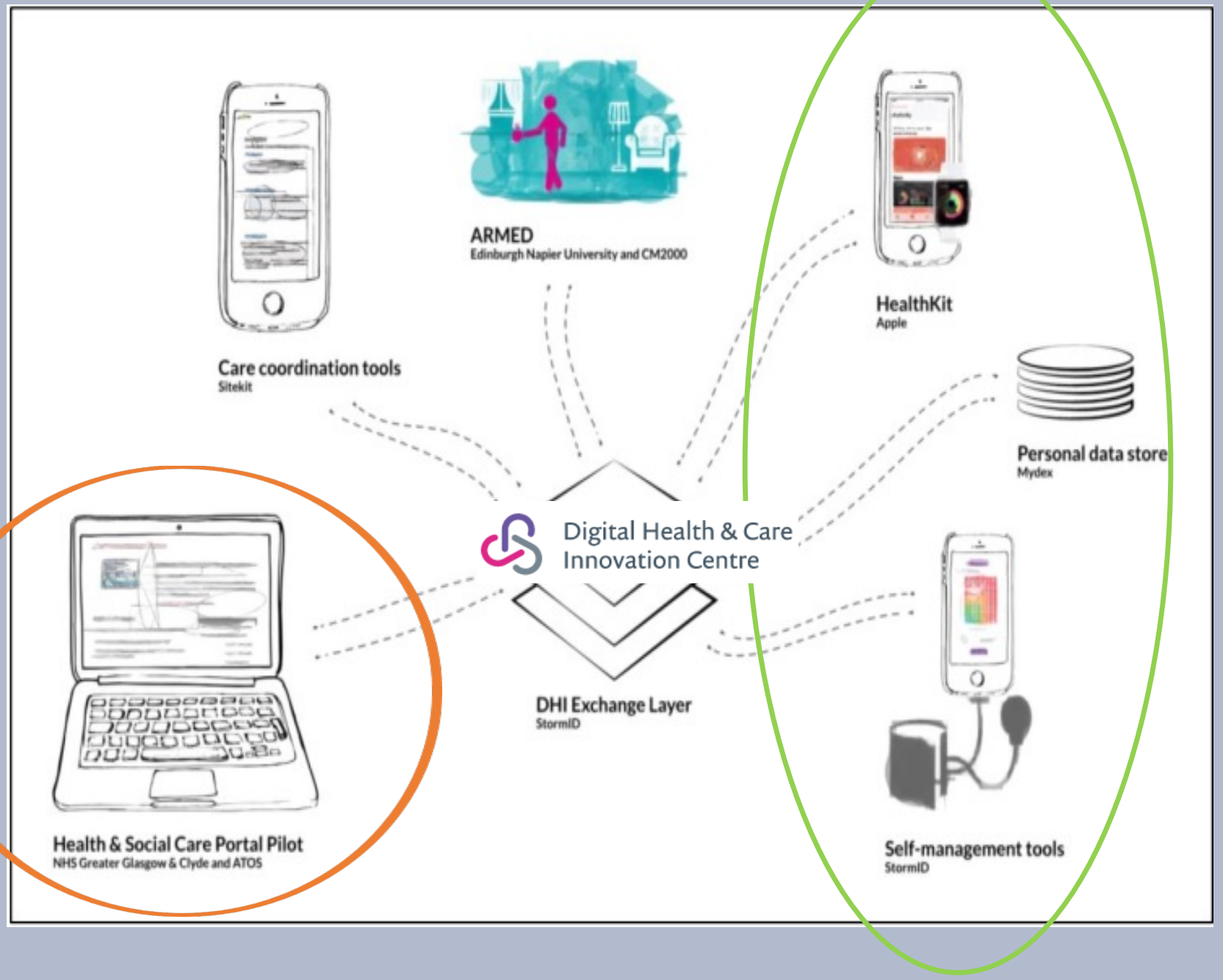
Consider in the last year:

never / seldom / sometimes / often / almost always

Social Care

+

NHS



Personal Healthcare

+

mHealth

Valid = Precise + Accurate

Device manufacture	reliability – physical factors
• sensors	transform mV to ^{0}C, wt, mmol/l; events to rate/hr
Manufacturer QA	sampling, batch selection → pricing
• calibrate	hardware with firmware (and updates)
Software in app	
• normalise output to standards	
• numeric	limits of normal, means, range
• classes	yes - no / good – bad / hi – normal - lo
• units	translations, also language
Single device / user	serialised data calibrates each device + user combo
Valid for healthcare	ACTION!

Summary

- These devices have good-enough Precision and Accuracy to be added into the mix of data sources we already use for clinical care
- Even cheap devices can be adequate when individual data is serialised
- Multiple devices' data can be munged together eg RHR on FitnessSync
- Traditional clinical data is also difficult to process in Risk Predictor tools by mental arithmetic
- Biological data is natively analogue but
- Device data is now digital and easily processed automatically on-device
- If we don't know how to mentally process this new data, we can send it to machine Risk Predictor tools to compute

- This mHealth data is already produced by millions of users outwith Health and Care systems
- Lifestyle users can integrate their data with other PHR
- All PHR data is curated by the user, asynchronously to NHS encounters, so
- NHS can promote these devices as
  - Contributing to PHR data, or
  - Direct use on NHS Platform, modelled on research platforms.
  - Supply bulk devices
    - SpO2
    - step/inactivity counters
    - RHR monitors