

e-Health & e-Epidemiology

how to improve population health
in the age of digital and **Artificial Intelligence?**

Guy Fagherazzi, MSc, PhD, HDR

Senior Research Scientist in Digital & Diabetes Epidemiology
CESP Inserm U1018

Twitter [@GFaghe](#) / Email guy.fagherazzi@gmail.com

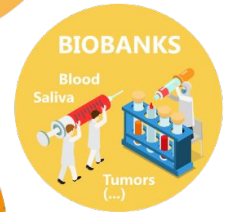
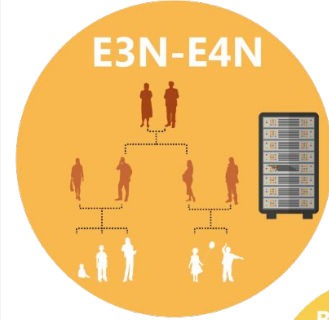
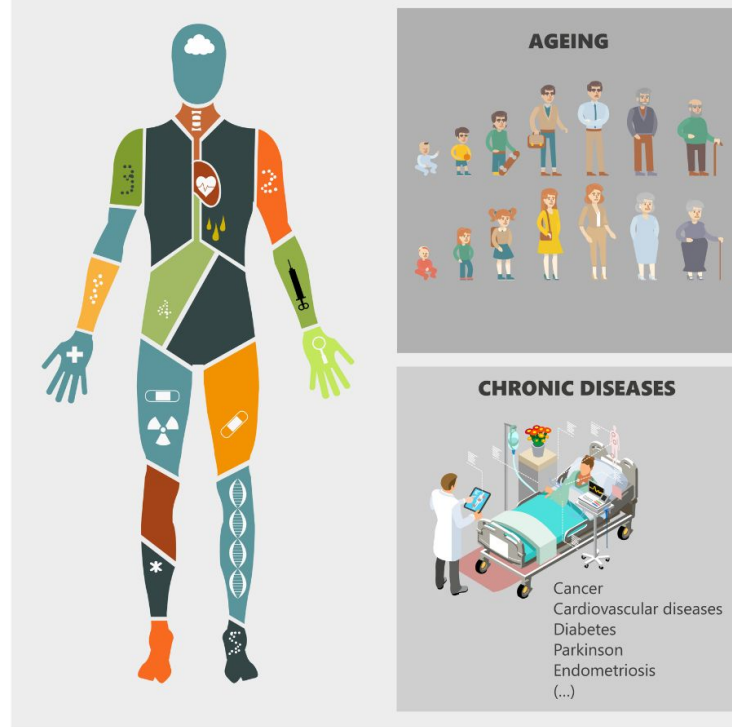
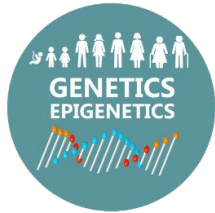




EXPOSOME

OUTCOMES

TOOLS





There is a new “omic” in town.

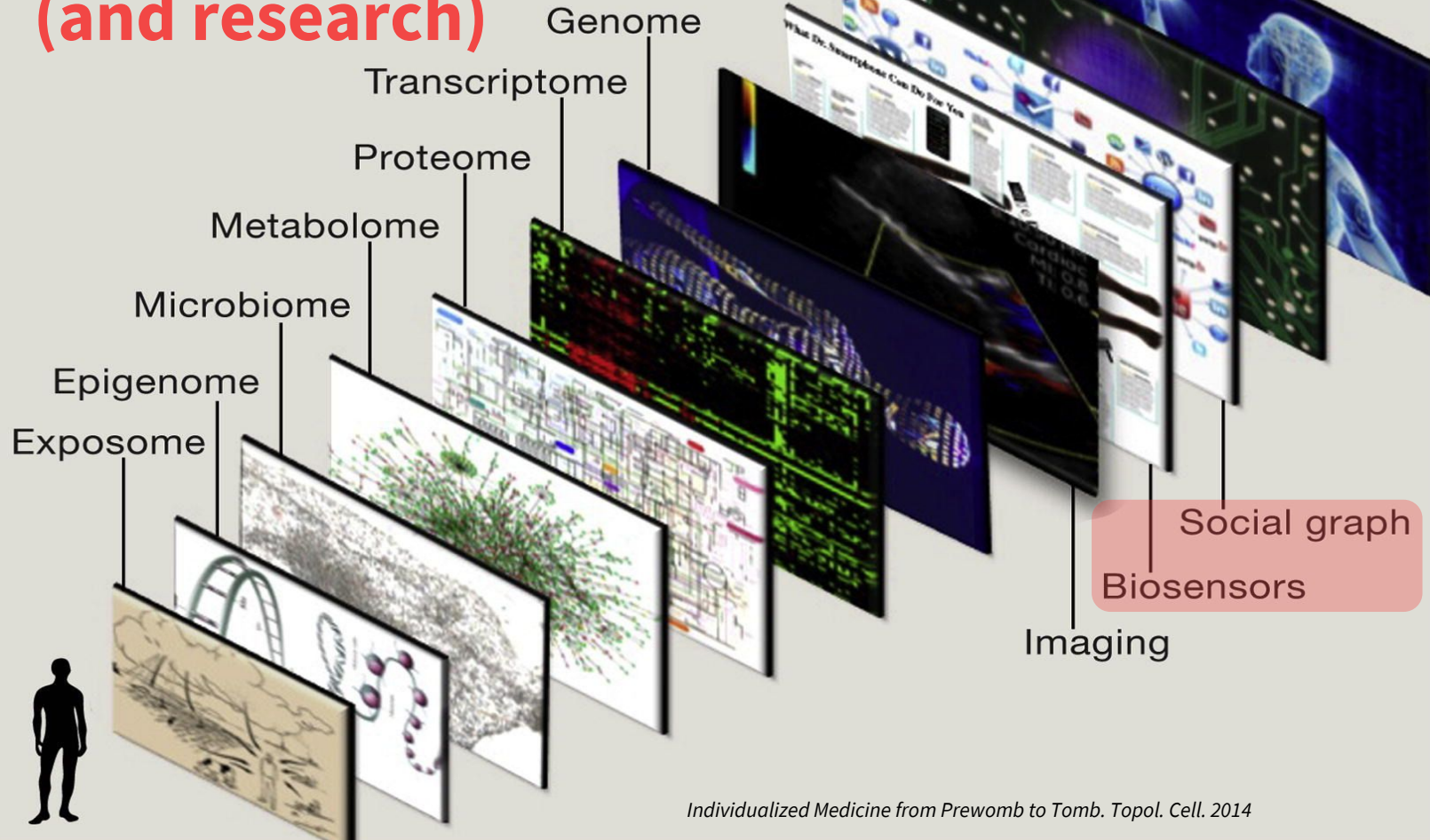
Genome
Epigenome
Proteome
Transcriptome
Metabolome
Microbiome

....

“DIGITOSOME”

= all the data generated
online by an individual
(smartphones, apps,
connected devices/sensors,
social media, geolocation)

Precision medicine (and research)



More & more data
A variety of
heterogeneous
“omic” data

Digitosome

Data generated
online by an
individual over the
lifecourse
(smartphones, apps,
connected devices,
social media, online
patients community...)

What are the challenges in epidemiology?

True for any past, present or future epidemiological study

Maximize recruitment & minimize attrition

Collect high-quality data on factors and outcomes of interest

Optimize logistics (costs of data acquisition, processing, analysis)

Cohort studies = gold standard

Prospective studies

No selection and recall bias

A close-up photograph of a hand holding a glowing lightbulb. The lightbulb is illuminated from within, casting a warm, orange glow. Overlaid on the lightbulb is a Venn diagram consisting of three overlapping circles. The top circle is pink and contains the text 'e-EPIDEMIOLOGY'. The bottom-left circle is yellow and contains the text 'DATA'. The bottom-right circle is teal and contains the text 'ARTIFICIAL INTELLIGENCE'. The circles overlap in the center, and a thin white line forms a partial circle around the intersection of the three circles.

e-EPIDEMIOLOGY

DATA

**ARTIFICIAL
INTELLIGENCE**

e-EPIDEMIOLOGY

DATA

**ARTIFICIAL
INTELLIGENCE**

History of cohort studies

40s-50s

(<10 000 participants)

First cohort studies

The Framingham Heart Study (1948)

The study of the Japanese atomic bomb survivors (1950)

70s

(10 000 - 100 000 participants)

First modern large cohort studies

The Nurses' Health Study (1976)

90s

(> 100 000 participants)

A new dimension in the design and the data collection

The Million Women Study UK (1996)

The E3N cohort study (1990)



The largest study on women's health in France

And one of the largest cohort studies in the world at the time

98 995 women + 28 years of follow-up

Self-reported questionnaires sent every 2-3 years since 1990

+ Rich biobank (25,000 blood & 47,000 saliva samples)

+ Medico-administrative database



Cancer



Diabetes



Nutrition



Reproductive

factors and hormones

Pioneer on the data acquisition in 1990

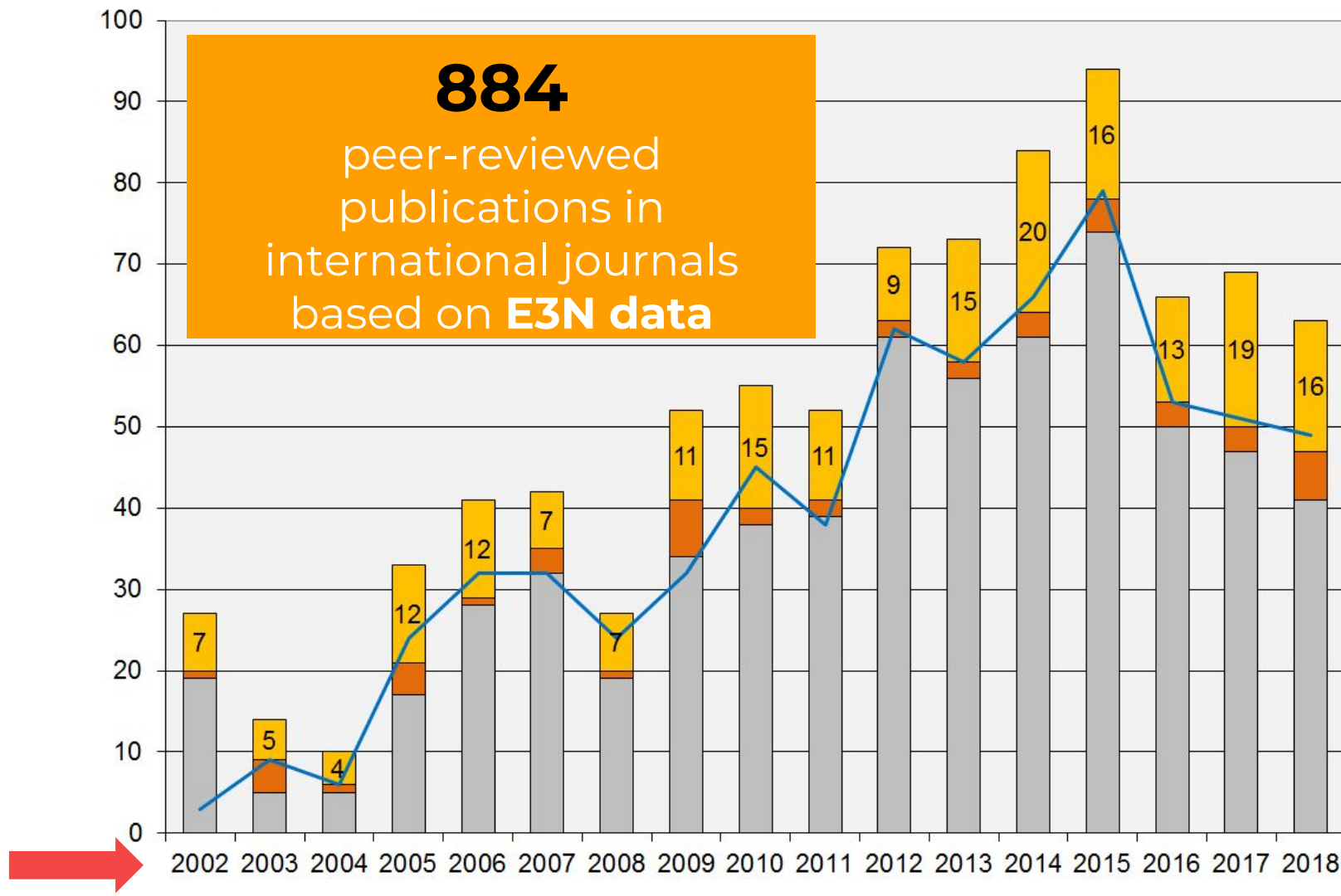
- Optical scan of paper questionnaires (Rate of 600 pages of questionnaires per hour)
- Systems of Automatic Document Reading & Character Recognition
- Video-coding and data checking

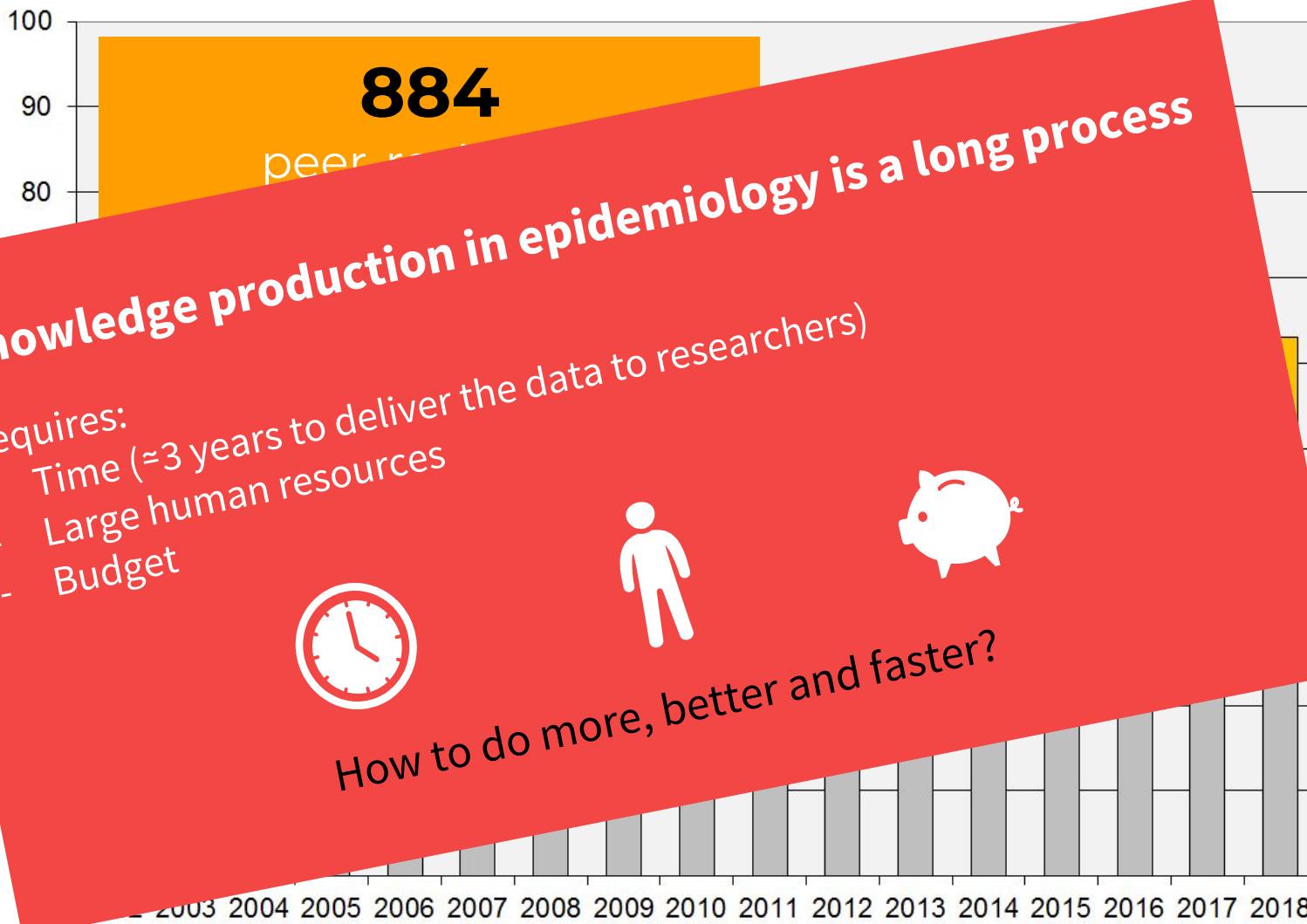
Ability to handle a large amount of data on many volunteers



884

peer-reviewed
publications in
international journals
based on **E3N data**





Knowledge production in epidemiology is a long process

It requires:

- Time (≈ 3 years to deliver the data to researchers)
- Large human resources
- Budget



How to do more, better and faster?

We need to kill the “Silo Effect”!



The “Silo Effect”

Up to 10 years between the idea and the publication

e-Epidemiology

The example of the E4N study





The E4N prospective study

A unique family cohort study!

Selected as an “*Investment for the Future*” by the French National Research Agency (ANR)



200 000
participants

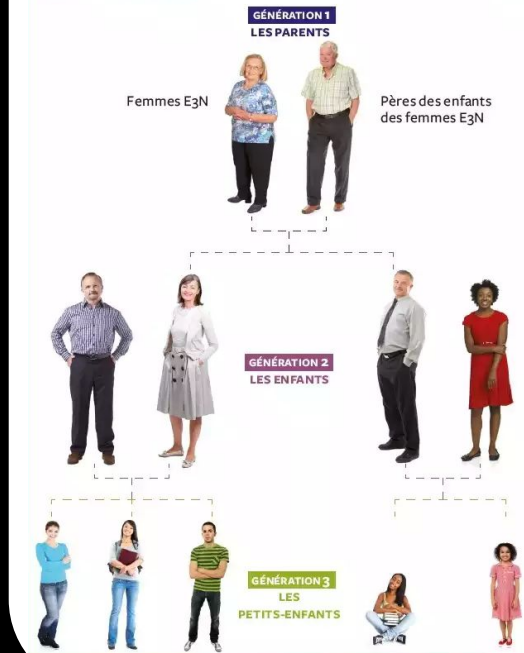
100 000 E3N women

20 000 fathers of E3N women's
children

50 000 children (*ongoing*)

20 000 grand-children (*in 2019*)

3 generations



1st generation: paper questionnaires

2nd & 3rd generations: e-cohort

Saliva samples for all the participants



Trans-generational

- Heredity and transmission of health determinants
- Genetics and epigenetics of chronic diseases (cancer, diabetes,...)

Expertise on exposures

- Epigenetics on lifestyle (smoking, physical activity, diet)
- Lifestyle and microbiota
- Socioeconomic mobility through generations and its impact on lifestyle and health

e-epidemiology

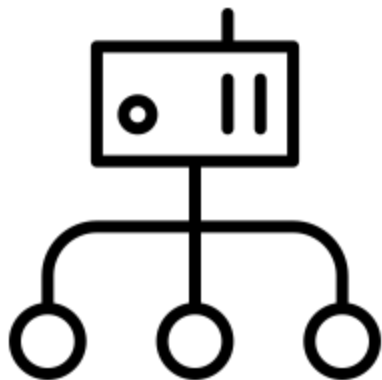
- Integrate new technologies and the Internet of Things in modern epidemiology to collect high-quality data

**Some research
axes**





Data Hub



epiconcept

smart health



Questionnaire



SMS



Smartphone



Biobank



SNDS
(M-A database)

The E4N Platform

- Short (but frequent) online questionnaires
- Answer from a laptop, smartphone or a tablet
- Questionnaires sent by SMS
- Sync with connected objects
- Automatic feedback and statistical dashboards for the participants
- Awards and badges (gamification)

A “connected” sub-cohort study



N = 700 E4N participants

Real-life study of lifestyle factors evaluated with a connected tracker

Study the associations between lifestyle factors and psychological well-being in participants with breast cancer or type 2 diabetes

Evaluation of the predictive capacity of the connected tracker data

Future extensions planned with other connected devices



Can we observe known associations with connected devices?



Journal of Medical Internet Research ISSN 1438-8871
The leading peer-reviewed journal for health and healthcare in the Internet age.
Open Access • Top Cited (Impact Factor: 4.5) • Rapid Peer-Review • Medline Indexed (+20 other indices)

Determinants of a poor sleep based on data from 15 000 users of connected devices

Guy Fagherazzi, PhD^{1,2}; Douae El Fatouhi, MSc^{1,2}; Alice Bellicha^{3,4}, MSc; Amin El-Gareh^{1,2}, MSc; Aurélie Affret, MSc^{1,2}; Courtney Dow, MPH^{1,2}; PhD; Lidia Delrieu, MSc^{5,6}; Matthieu Vegreville, MSc⁷; Alexis Normand, MSc⁷; Jean-Michel Oppert, MD, PhD³; Gianluca Severi, PhD^{1,2}

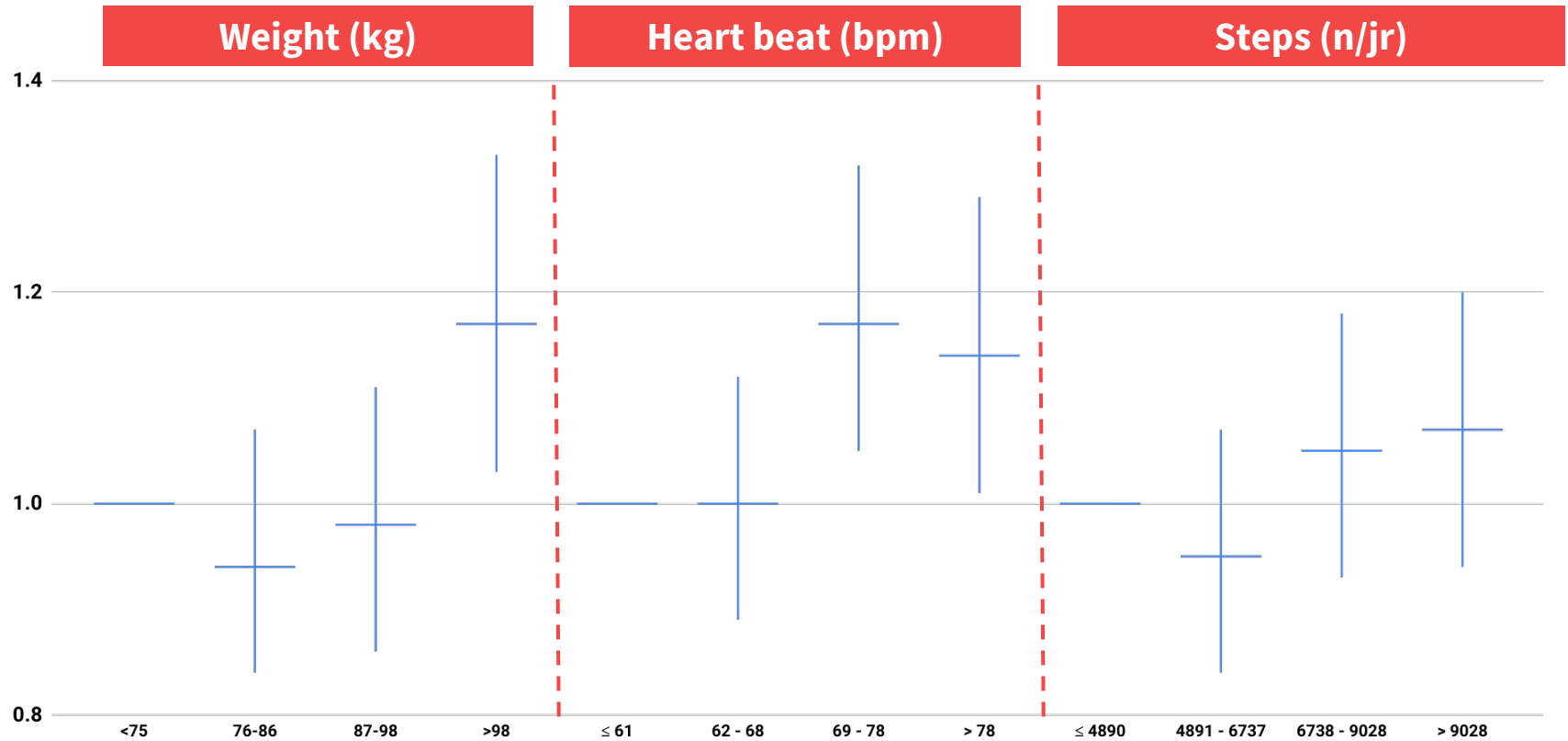
Data from “hyperconnected” users of Withings/Nokia devices between 2013 and 2016
15 839 individuals (13 658 men & 2 181 women)

AI clustering methods (ongoing)

Data

Sleep (Total, Deep, Ratio Deep/total), Age, Sex, Weight, Nb of steps, Heart beat, Blood pressure

Determinants of short sleep duration ($\leq 6h$)



Other great e-epidemiology initiatives

In France and in the USA



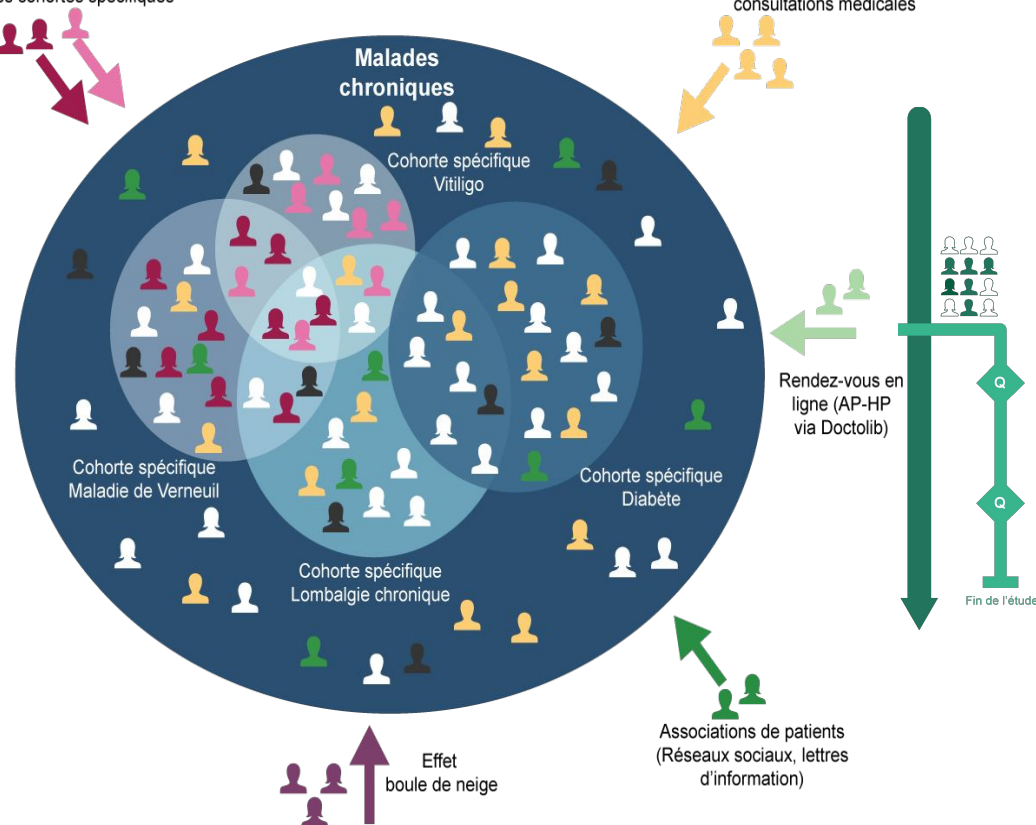
“1 study to rule them all”

An umbrella cohort for patients with any chronic disease(s)

- ▶ Study on **multimorbidity, burden of treatment/diseases, PROs**
- ▶ **Web platform** (e-questionnaires)
- ▶ Matching ongoing with the AP-HP Data Warehouse and national MA databases
- ▶ Patient recruitment for **TWICs (Trials WithIn Cohorts)**
- ▶ Patients contribute to define the research questions to investigate thanks to the [Inspire](https://inspire.ap-hp.fr/) platform
- ▶ New model of collaborative and mutualized research
<https://compare.ap-hp.fr/>

Recrutement via les équipes de recherche pilotant les cohortes spécifiques

Affiches dans les consultations médicales



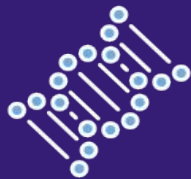
2010 and beyond: the mega-cohorts



environment



lifestyle



biology

+ 1,000,000 participants

WE'VE MAPPED THE WORLD. NOW LET'S MAP HUMAN HEALTH.



MY MOOD TODAY



Enthusiastic

80%

Scared

20%

MY SLEEP LAST NIGHT



Times awakened

2

Sleep duration

7.5 hr

MY HEARING TEST



Left ear

Normal

Right ear

Normal

MY ECG TODAY



Heart rate

72 bpm

PR Interval

0.17

MY DIET TODAY



Coffee

2 cups

Water

8 cups

MY IMMUNIZATION RECORD



Tetanus

Yes

Pertussis

Yes



 **Project Baseline**

**The birth of
AI-oriented
cohorts**

10 000
participants

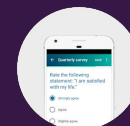
Yearly clinical visits
+ biobank
+ connected devices

verily

 **Duke University
School of Medicine**

 **Stanford
MEDICINE**

Google



A close-up photograph of a hand holding a glowing lightbulb. The lightbulb is illuminated from within, casting a warm, orange glow. Overlaid on the lightbulb is a Venn diagram consisting of three overlapping circles. The top circle is light gray and contains the text 'e-EPIDEMIOLOGY'. The bottom-left circle is bright yellow and contains the text 'DATA'. The bottom-right circle is light gray and contains the text 'ARTIFICIAL INTELLIGENCE'. The three circles overlap in the center, and the entire diagram is set against the dark background of the hand and the lightbulb's interior.

e-EPIDEMIOLOGY

DATA

**ARTIFICIAL
INTELLIGENCE**

The Data Rush

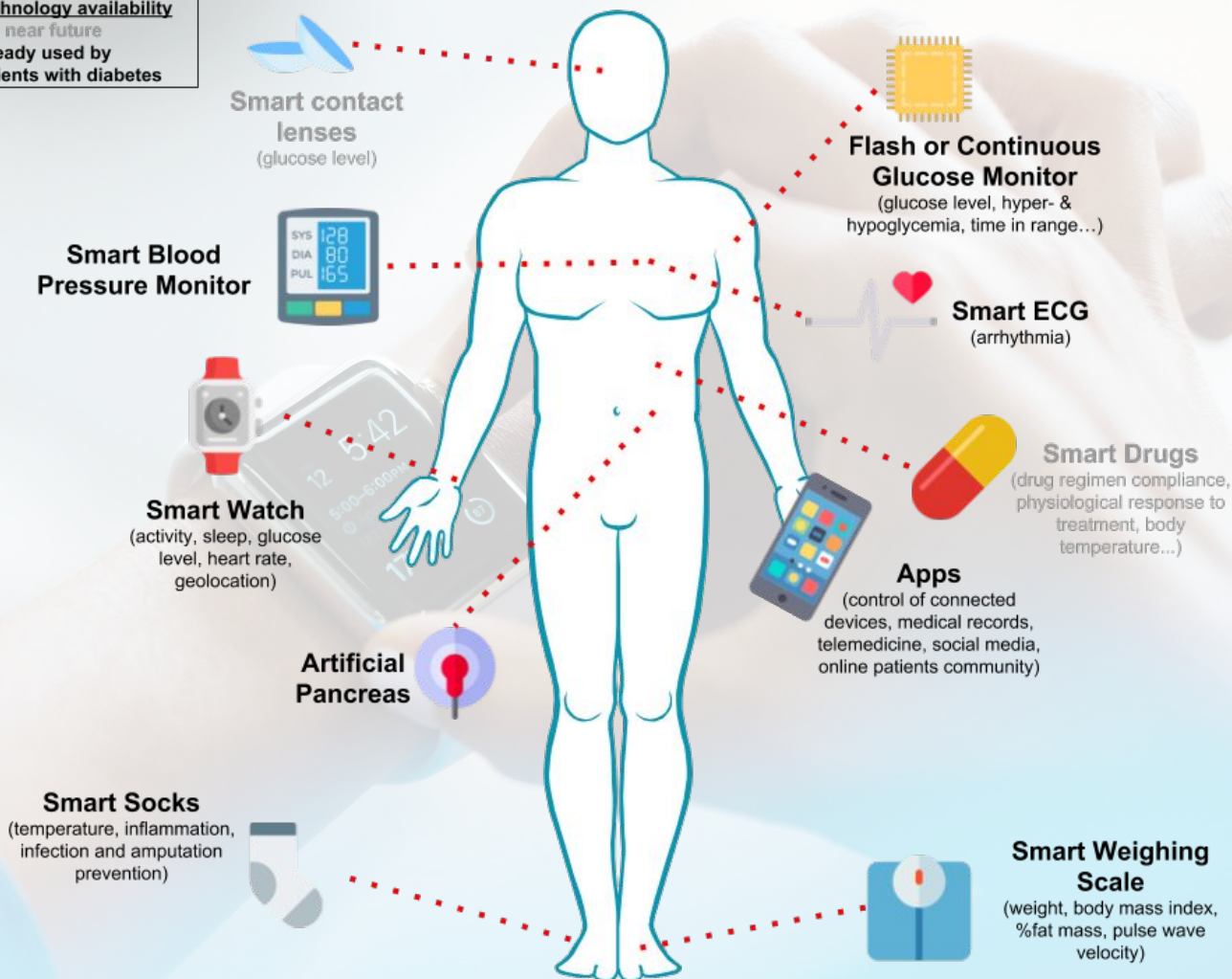


*Technological innovation drives
modern epidemiological research*



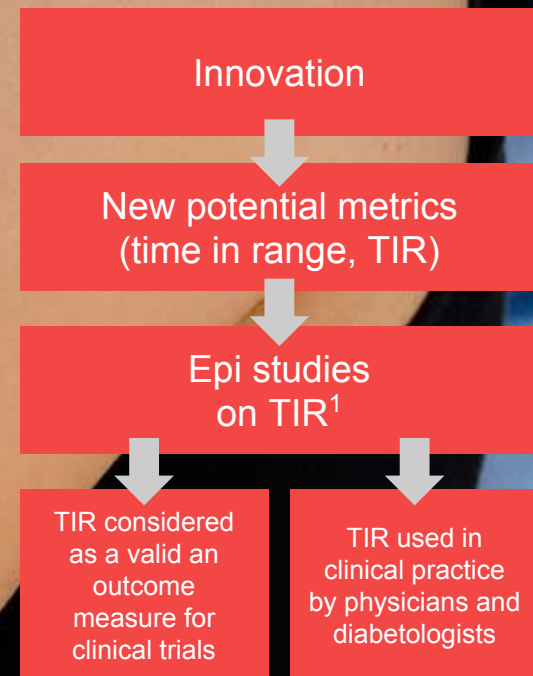
New data sources in medical research

Technology availability
In a near future
Already used by
patients with diabetes



Digital diabetes: perspectives for diabetes prevention, management and research. Fagherazzi et al. ([Diabetes & Metabolism, 2018](#)) - Open Access

Digital & technological innovation: from epi studies to clinical practice

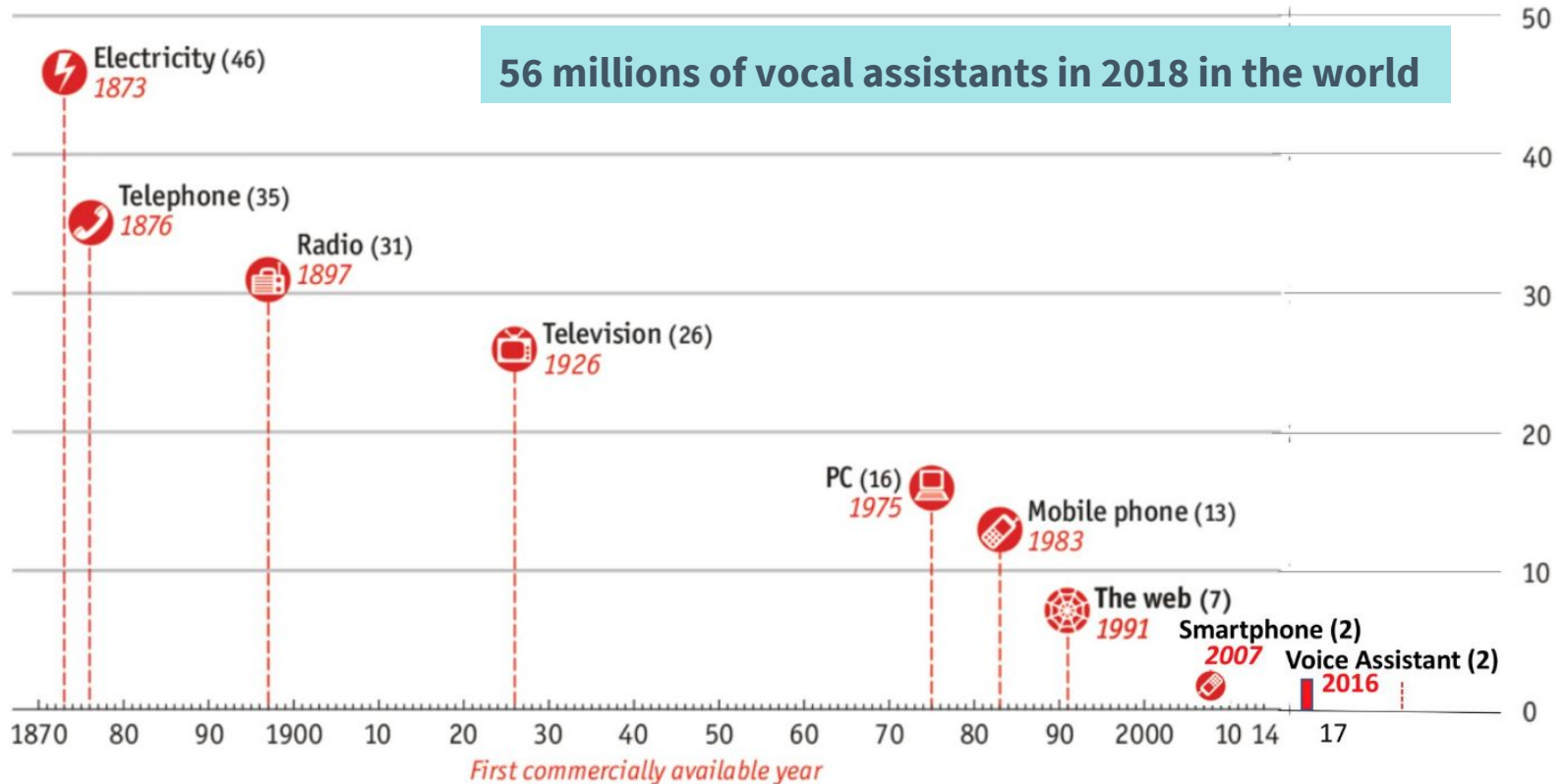


1. Roy W. Beck et al. Diabetes Care 2018 Oct. Validation of Time in Range as an Outcome Measure for Diabetes Clinical Trials
<http://care.diabetesjournals.org/content/early/2018/10/17/dc18-1444>

Vocal biomarkers: “the next big thing”?

Technology adoption

Years until used by one-quarter of American population



Vocal biomarkers: “the next big thing”?



Voice Signal Characteristics Are Independently Associated With Coronary Artery Disease

Elad Maor, MD, PhD; Jaskanwal D. Sara, MBChB; Diana M. Orbelo, PhD;
Lilach O. Lerman, MD, PhD; Yoram Levanon, PhD; and Amir Lerman, MD

Will be useful for

- Study of emotions and feelings of patients/study participants
- Early markers of risk -> prevention
- Diagnostic markers

Mental health / Neurodegenerative diseases / Cardiometabolic diseases

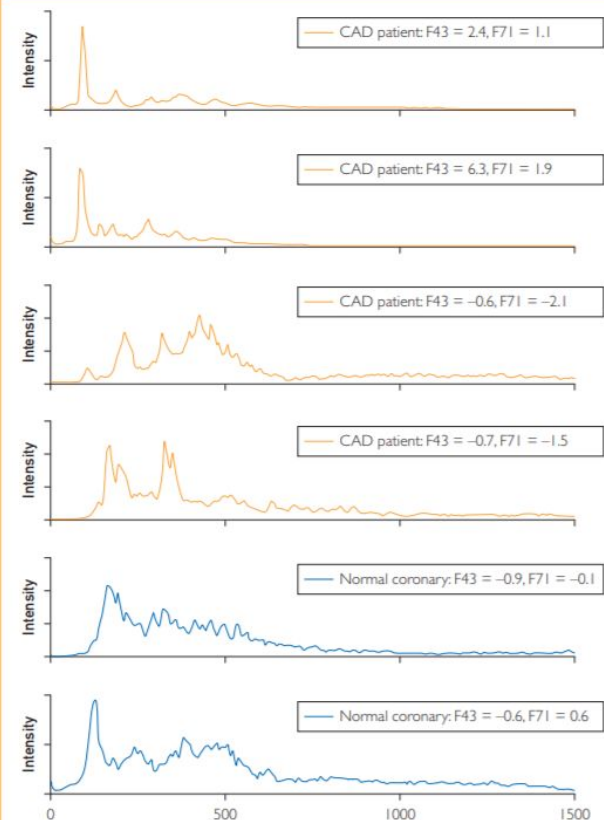


FIGURE 1. Power spectrum density plots of patients with CAD and controls. Examples of PSD of patients with and without CAD. All examples are from the third recording (negative emotional experience). The graphs show cases of patients with normal coronaries, patients with extreme decay/asymmetry of feature 43, and patients with extreme values of feature 71. Features are calculated by averaging over time the instantaneous PSD values calculated using Fourier transform on 25-ms frames with 10-ms shift. CAD = coronary artery disease; PSD = power spectrum density.

E-health records and medico-administrative databases

French administrative databases

- ▶ **SNIIRAM** (national health insurance database = claims, medical acts...)
- ▶ **PMSI** (national hospital discharge database)
- ▶ **Causes of death**

(No clinical/biological data)

Covers 96% of the French population



Health Data Warehouses (AP-HP, Paris)

- ▶ 8 millions of patients per year
- ▶ Hospital discharge database + clinical/biological/imaging results
- ▶ Used for observational studies, feasibility studies for clinical trials

Used alone = limited interest / Matched with cohorts = huge potential

And tomorrow?

The French “Health Data Hub” will gather:

- ▷ French administrative databases
- ▷ Data from publicly funded research projects (cohorts, registries...)
- ▷ DMP (Personalized e-health records)
- ▷ Connected devices

- ▷ **Interoperability?**
- ▷ **Governance?**
- ▷ **Accessibility?**
- ▷ **Security?**
- ▷ **Sustainability?**
- ▷ **Consent from patients?**



**HEALTH
DATA
HUB**

<https://solidarites-sante.gouv.fr/ministere/documentation-et-publications-officielles/rapports/sante/article/rapport-health-data-hub-mission-de-prefiguration>

A close-up photograph of a hand holding a glowing incandescent lightbulb. The light from the bulb illuminates the hand and the background. Overlaid on the image is a Venn diagram consisting of three overlapping circles. The top circle is light gray and contains the text 'e-EPIDEMIOLOGY'. The bottom-left circle is also light gray and contains the text 'DATA'. The bottom-right circle is a vibrant teal color and contains the text 'ARTIFICIAL INTELLIGENCE'. White curved lines connect the circles, forming a triangular shape around the central intersection of all three.

e-EPIDEMIOLOGY

DATA

**ARTIFICIAL
INTELLIGENCE**

The use of **AI** in epidemiology & population health studies

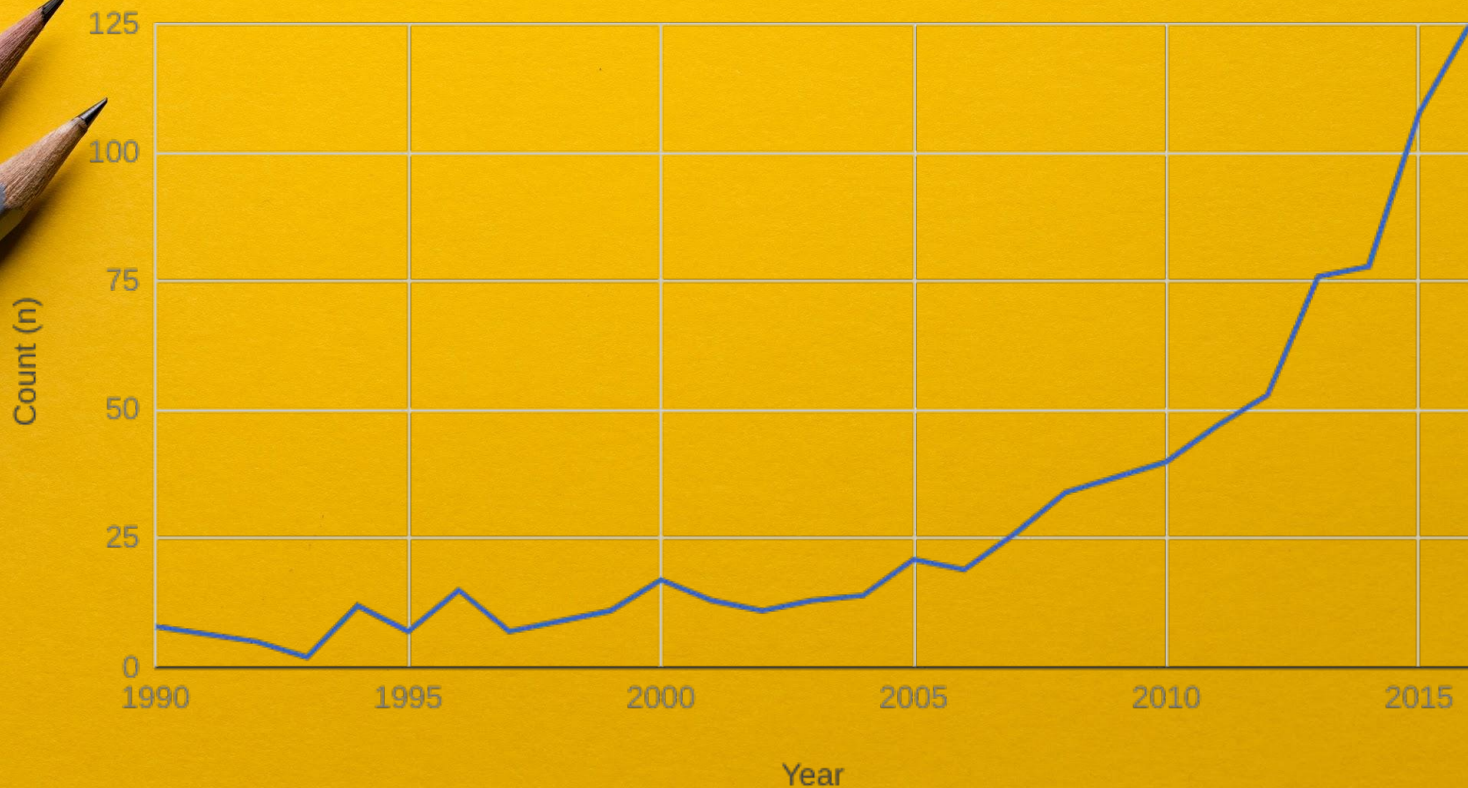
New opportunities



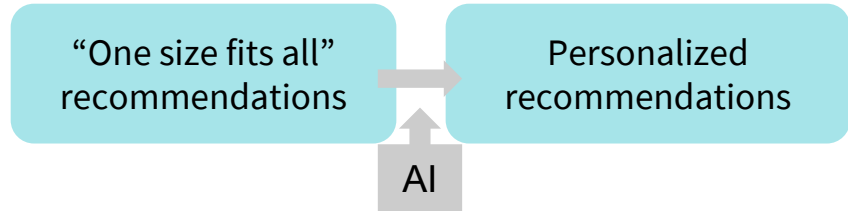
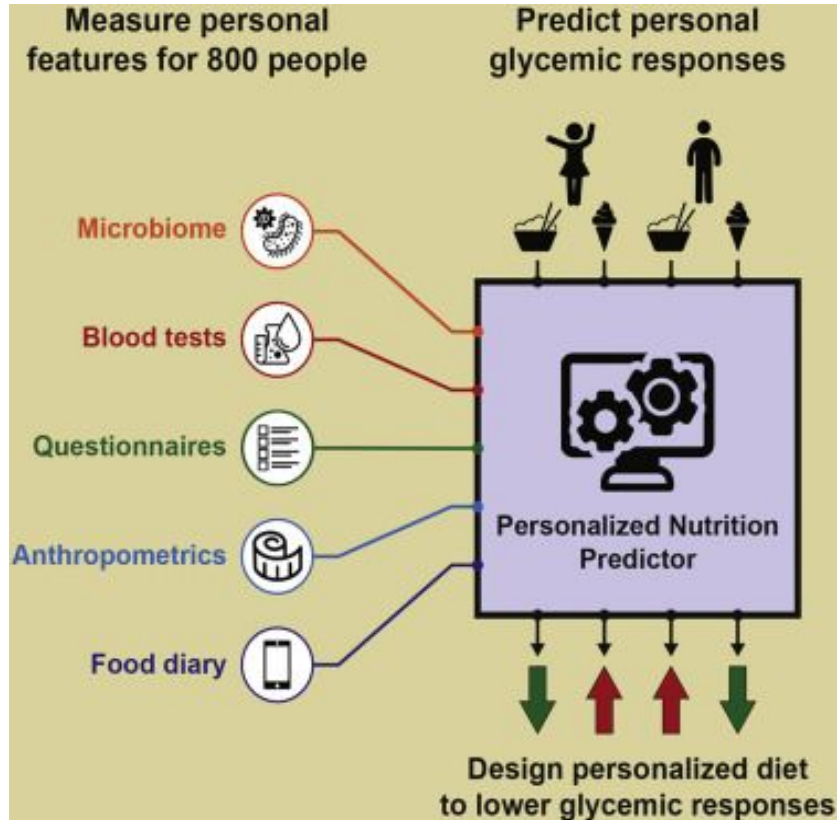
AI

A changing
landscape

Artificial Intelligence and Diabetes - Pubmed Search



Nutrition & Type 2 diabetes



Fact: there is a large individual inter and intra-variability in the glycemic response to a given meal

Data: Continuously monitored week-long glucose levels in an 800-person cohort, measured responses to 46,898 meals

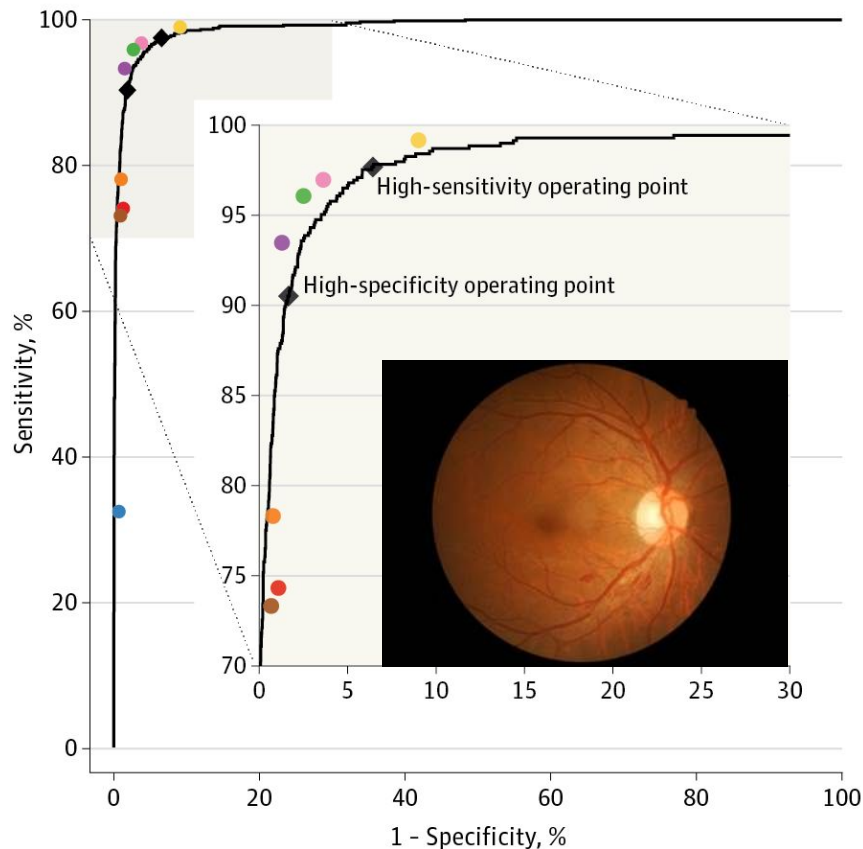
Solution: prediction of the glycemic response using **machine-learning** models based on blood parameters, dietary habits, anthropometrics, physical activity, and gut microbiota

*Personalized Nutrition by Prediction of Glycemic Responses.
David Zeev et al. Cell 2015*



Diagnosis of diabetic retinopathy

A EyePACS-1: AUC, 99.1%; 95% CI, 98.8%-99.3%



Diagnosis by human experts

Automated diagnosis

AI

9963 retinal fundus photographs annotated by 7 experts

AUC

Sensitivity

Specificity

99,1%

97,5%

93,4%

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. Gulshan et al. JAMA 2015

AI as a tool to do more than what the humans can do



(Almost) perfect prediction of gender from retinal fundus photographs

Predicted risk factor (evaluation metric)	UK Biobank validation dataset ($n = 12,026$ patients)	
	Algorithm	Baseline
	(95% CI)	
Age: MAE, years (95% CI)	3.26 (3.22,3.31)	7.06 (6.98,7.13)
Age: R^2 (95% CI)	0.74 (0.73,0.75)	0.00
Gender: AUC (95% CI)	0.97 (0.966,0.971)	0.50



Actual: Female
Predicted: Female

The special case of social media data in epidemiology

AI and textual data



The digital epidemiology - You are what you Tweet

“Social media, such as Twitter, can be used to access local and timely information about **disease outbreaks** and **related events** around the world”

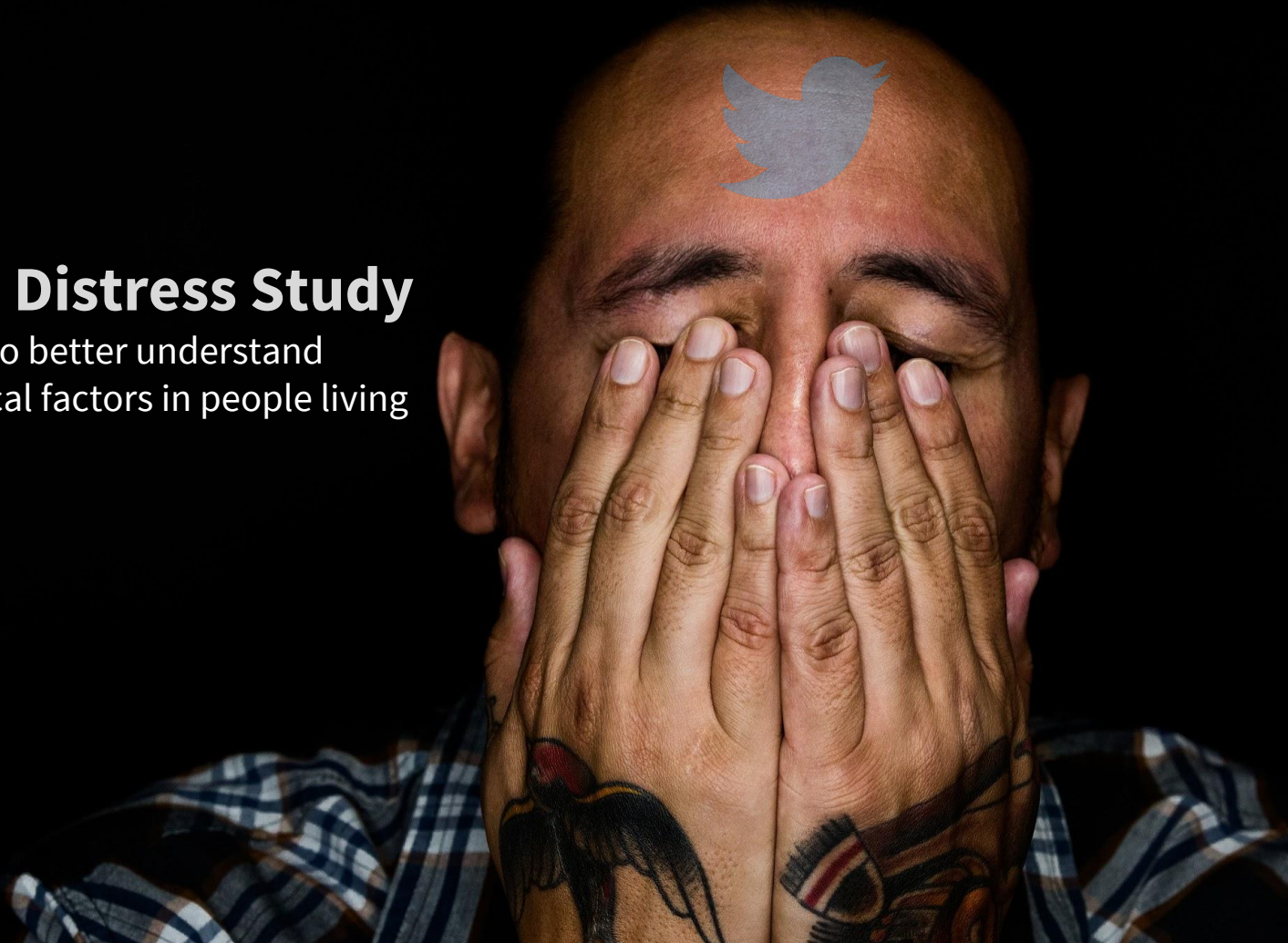
Marcel Salathé,
EPFL Lausanne

One of the founding fathers



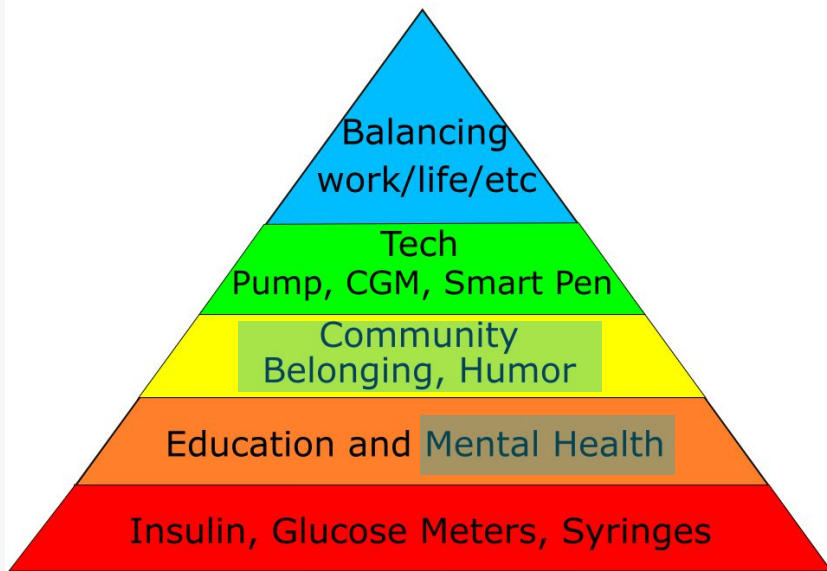
World Diabetes Distress Study

The use of **Twitter** and **AI** to better understand emotions and psychological factors in people living with diabetes



Why working on this topic?

Type 1 diabetes



by @MTL613

Type 2 diabetes

Priority 4

How do stress and anxiety influence the management of Type 2 diabetes and does a positive mental wellbeing have an effect?



Priority 9

How can psychological or social support be best used to help people with, or at risk of Type 2 diabetes, and how should this be delivered to account for individual needs?



DiABETES UK
KNOW DIABETES. FIGHT DIABETES.

Diabetes distress



	Not a problem	Minor problem	Moderate problem	Somewhat serious problem	Serious problem
1. Not having clear and concrete goals for your diabetes care?	0	1	2	3	4
2. Feeling discouraged with your diabetes treatment plan?	0	1	2	3	4
3. Feeling scared when you think about living with diabetes?	0	1	2	3	4
4. Uncomfortable social situations related to your diabetes care (e.g., people telling you what to eat)?	0	1	2	3	4
5. Feelings of deprivation regarding food and meals?	0	1	2	3	4
6. Feeling depressed when you think about living with diabetes?	0	1	2	3	4
7. Not knowing if your mood or feelings are related to your diabetes?	0	1	2	3	4
8. Feeling overwhelmed by your diabetes?	0	1	2	3	4
9. Worrying about low blood sugar reactions?	0	1	2	3	4
10. Feeling angry when you think about living with diabetes?	0	1	2	3	4
11. Feeling constantly concerned about food and eating?	0	1	2	3	4
12. Worrying about the future and the possibility of serious complications?	0	1	2	3	4
13. Feelings of guilt or anxiety when you get off track with your diabetes management?	0	1	2	3	4
14. Not "accepting" your diabetes?	0	1	2	3	4
15. Feeling unsatisfied with your diabetes physician?	0	1	2	3	4
16. Feeling that diabetes is taking up too much of your mental and physical energy every day?	0	1	2	3	4
17. Feeling alone with your diabetes?	0	1	2	3	4
18. Feeling that your friends and family are not supportive of your diabetes management efforts?	0	1	2	3	4
19. Coping with complications of diabetes?	0	1	2	3	4
20. Feeling "burned out" by the constant effort needed to manage diabetes?	0	1	2	3	4

PAID

Problem Areas In Diabetes)

Limitations

- Self-reported
- Non evolutive
- Some components of DD are missing (work-related issues, cost of treatment, HCP relationships...)
- Interpreted with a HCP
- "Make my doctor happy" effect
- Risk of denial and bias

Change of
paradigm

Let's analyze what people with diabetes are saying
online.

All over the world.

- “Let’s use Twitter!”
- “But... why Twitter?”
- “Well...because Twitter!”



Key figures

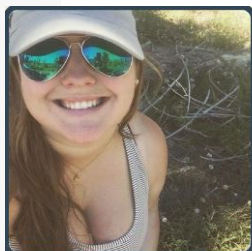
- ▷ 313 millions/months of active users
- ▷ > 4,7 millions of people are actually tweeting
- ▷ Data coming from the entire world
- ▷ Public data by default

Languages on Twitter

- ▷ English (34%)
- ▷ Japanese (16%)
- ▷ Spanish (12%)
- ▷ Malay (8%)
- ▷ Portuguese(6%)
- ▷ Arab (6%)
- ▷ French(2%)

Diabetes Online Community on Twitter

Data unavailable in a traditional clinical setting

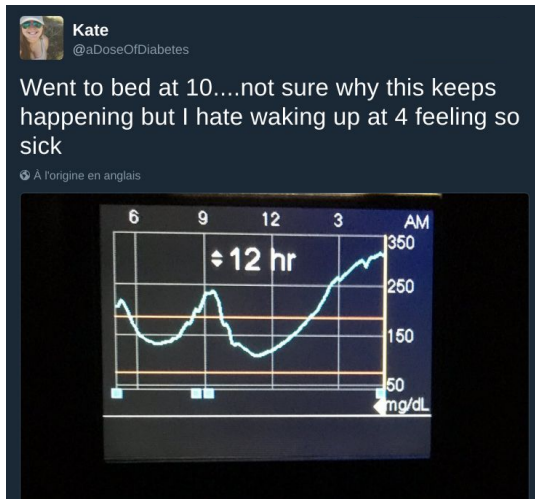


Kate

@aDoseOfDiabetes

26 years old. type 1 diabetic for 25 years. I like pretty things and nice people.

California, USA



JllyJllyFish Retweeted



EnvyDaTropic™ @envydatropic

il y a 3 jours

If it doesn't clog arteries or cause diabetes I'm not eating it

152 203



Pat Atarte @UnSdfEnCorse · 2 min

Tant d'années de combat contre les glycémies à stabiliser, un sentiment de fatigue apparaît souvent, de la lassitude à être tout le temps aux aguets, à être différent des autres...Même si cela ne se voit pas ! Je suis malade.. Et sérieusement.. #diabete



MeaT @TimeaTheTranny

Il y a 13 mins

Everytime i feel a minor ache in my foot i assume it's because of diabetes.

5



Type1bri @type1bri · 18 févr.

My latest flourey with the libre to check basal and ratios has been a success, no changes needed atm until next time #gbdoc #doc #ourd

À l'origine en anglais



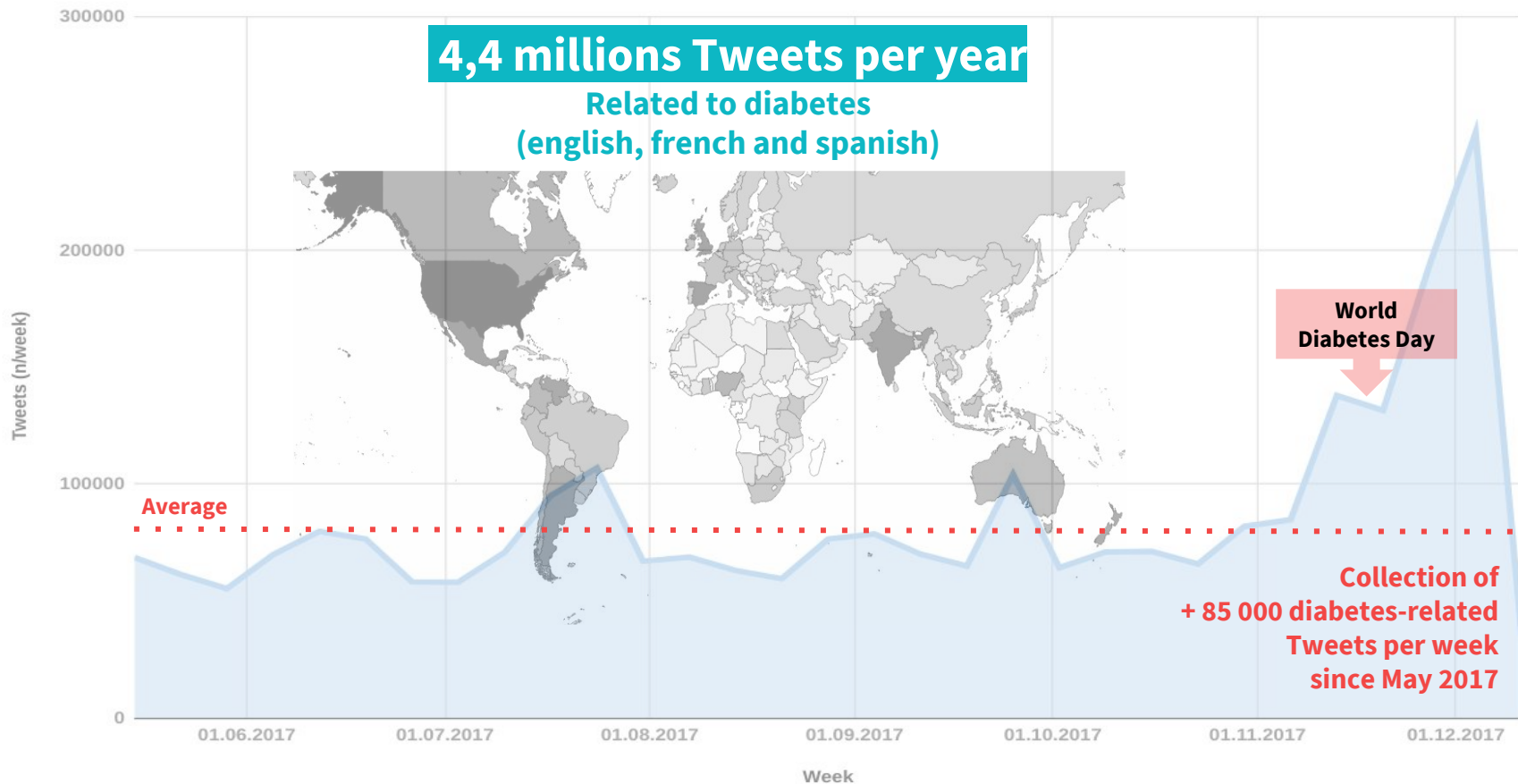
Tasha @tasha_louise

Il y a 15 mins

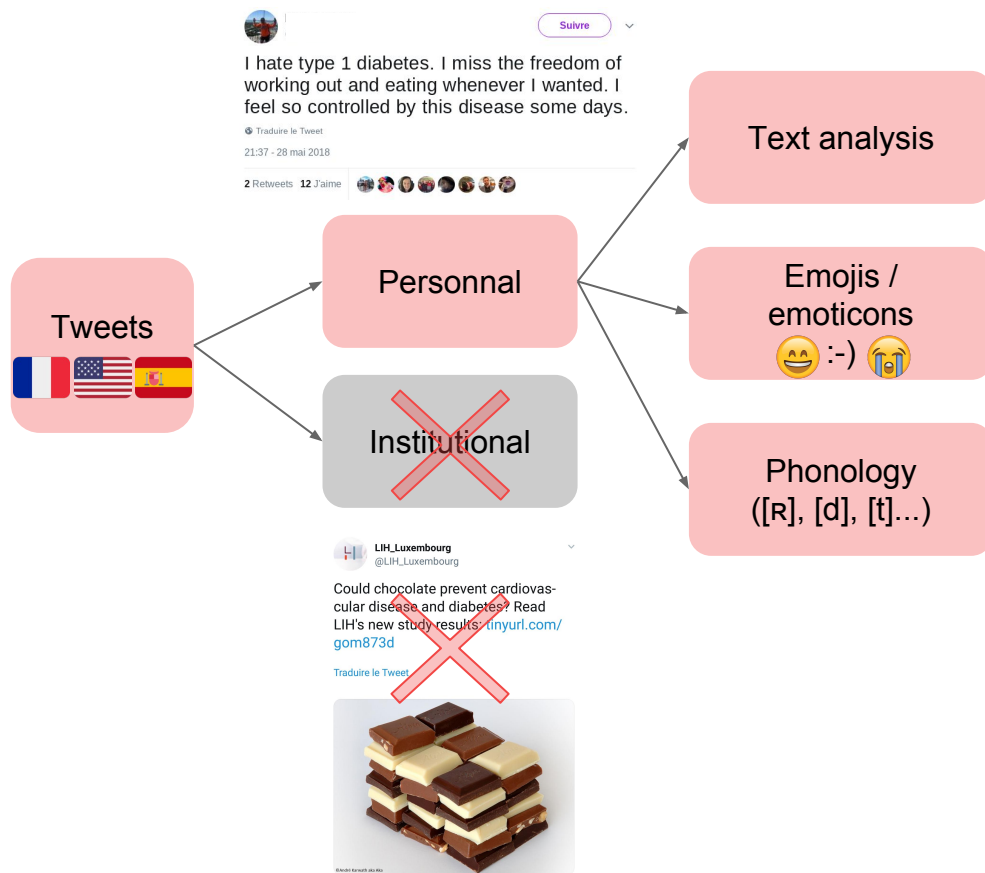
Just because you can't SEE my conditions, does not mean they're not there #diabetes #mentalhealth #longstandingillness

5

Data collection



Methodology



Topic modeling (Latent Dirichlet Allocation)

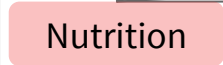
Sentiment analysis

Clustering of diabetes distress patterns (AI, NLP)

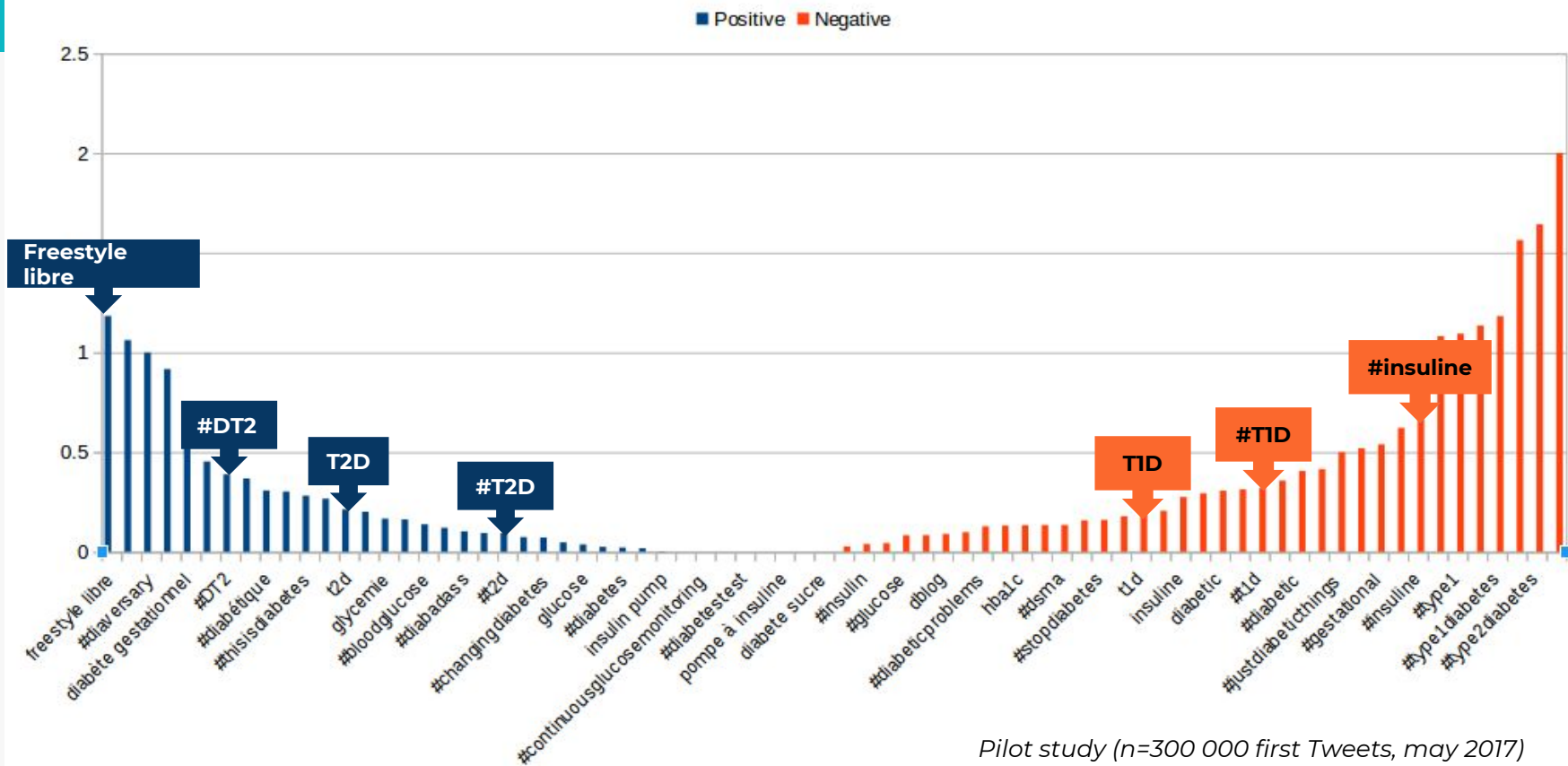
Spatial analysis



100



Sentiment analysis on frequent hashtags

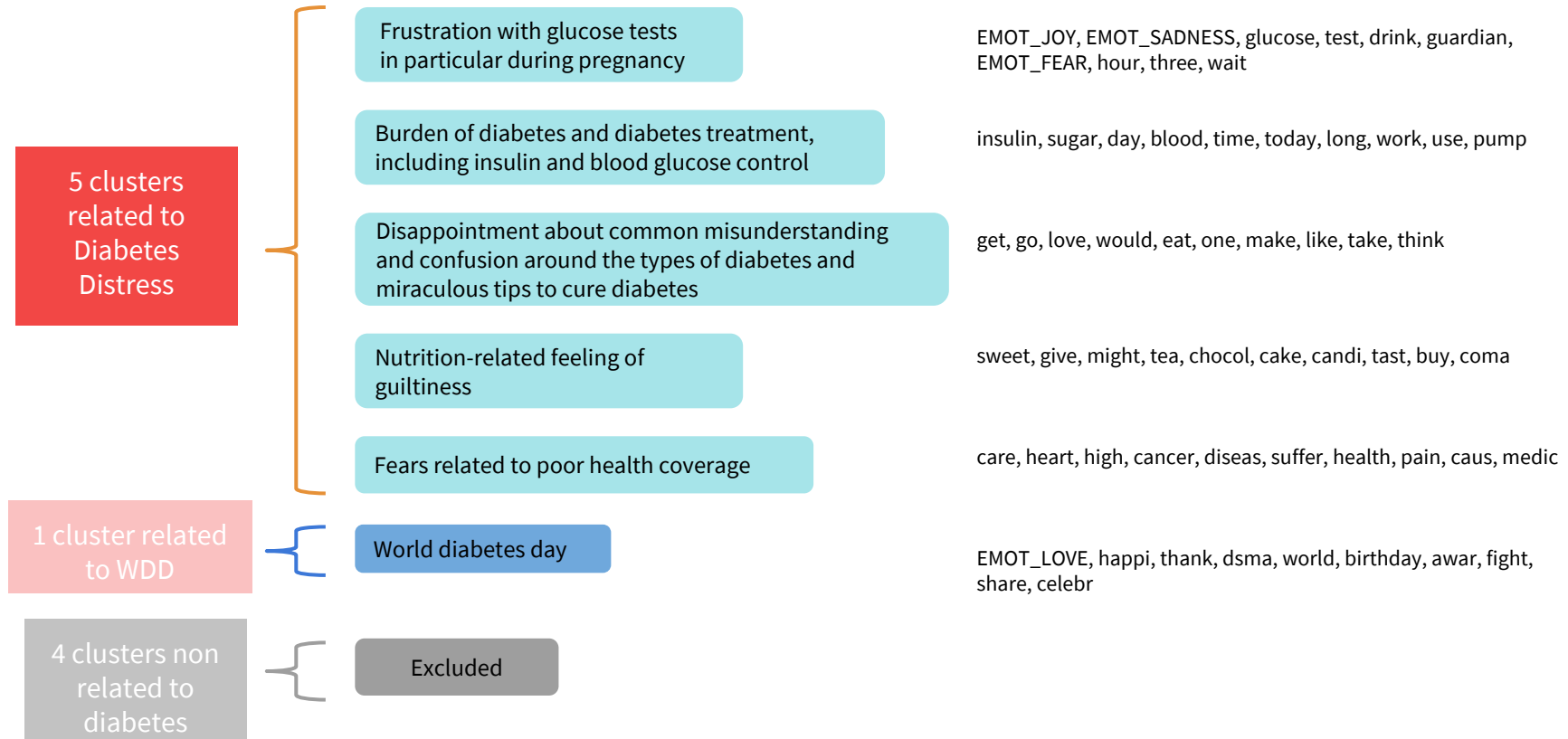


Diabetes Distress Patterns and related emotions

- ▶ **Classification of emotions** by Parrott
- ▶ Used diabetes-related Tweets with emotions (N=129 313)
- ▶ Gather all the synonyms of these emotions
- ▶ Clustering method (**LDA**) -> **10 clusters**

Primary emotion	Secondary emotion	Tertiary emotions
Love	Affection	Adoration, affection, love, fondness, liking, attraction, caring, tenderness, compassion, sentimentality
	Lust	Arousal, desire, lust, passion, infatuation
	Longing	Longing
Joy	Cheerfulness	Amusement, bliss, cheerfulness, gaiety, glee, jolliness, joviality, joy, delight, enjoyment, gladness, happiness, jubilation, elation, satisfaction, ecstasy, euphoria
	Zest	Enthusiasm, zeal, zest, excitement, thrill, exhilaration
	Contentment	Contentment, pleasure
	Pride	Pride, triumph
	Optimism	Eagerness, hope, optimism
	Enthrallment	Enthrallment, rapture
	Relief	Relief
Surprise	Surprise	Amazement, surprise, astonishment
Anger	Irritation	Aggravation, irritation, agitation, annoyance, grouchiness, grumpiness
	Exasperation	Exasperation, frustration
	Rage	Anger, rage, outrage, fury, wrath, hostility, ferocity, bitterness, hate, loathing, scorn, spite, vengefulness, dislike, resentment
	Disgust	Disgust, revulsion, contempt
	Envy	Envy, jealousy
	Torment	Torment
Sadness	Suffering	Agony, suffering, hurt, anguish
	Sadness	Depression, despair, hopelessness, gloom, glumness, sadness, unhappiness, grief, sorrow, woe, misery, melancholy
	Disappointment	Dismay, disappointment, displeasure
	Shame	Guilt, shame, regret, remorse
	Neglect	Alienation, isolation, neglect, loneliness, rejection, homesickness, defeat, dejection, insecurity, embarrassment, humiliation, insult
	Sympathy	Pity, sympathy
Fear	Horror	Alarm, shock, fear, fright, horror, terror, panic, hysteria, mortification
	Nervousness	Anxiety, nervousness, tenseness, uneasiness, apprehension, worry, distress, dread

Diabetes Distress Patterns and related emotions



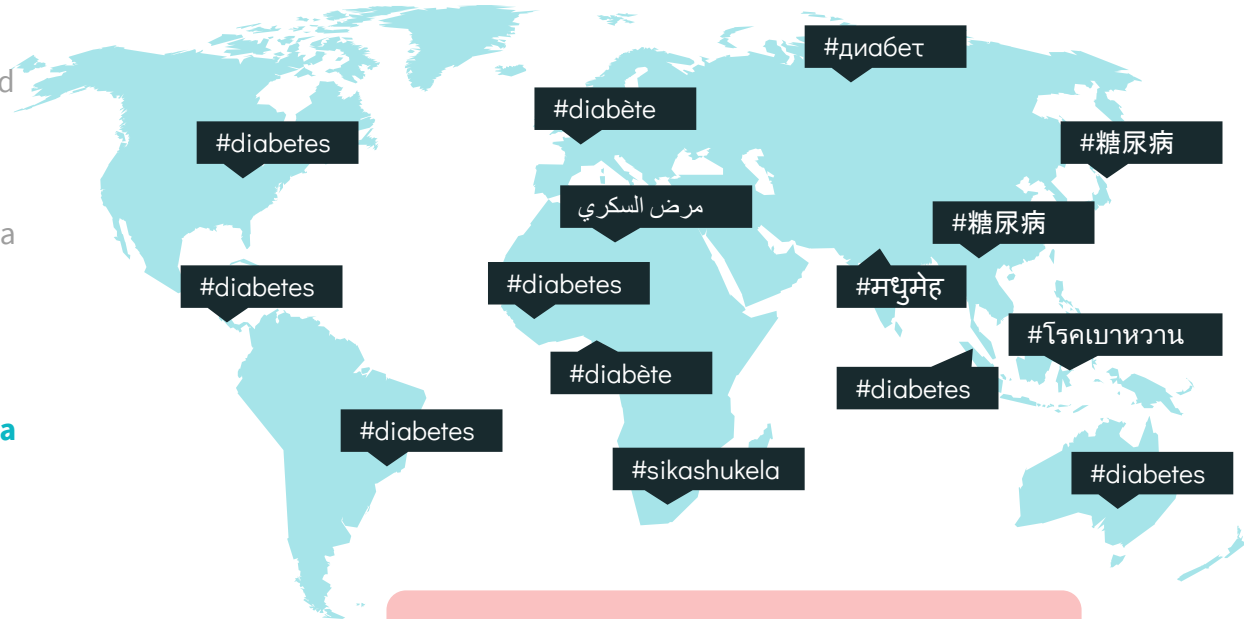
Worldwide e-cohort study

e-cohort

- ▷ Targeted online recruitment
- ▷ Creation of an independent and secured web platform
- ▷ Prospective data collection on lifestyle and psychological factors and health events with a **chatbot**

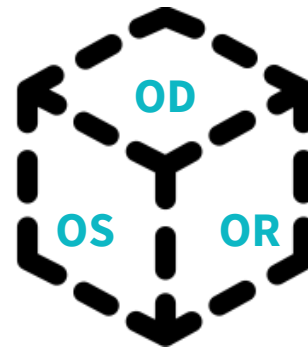
Sync connected devices

Match with third-party open databases based on geolocation data



Open Source/Open Data project

Encourage open medical research



Open Data

Datasets

Open Source

Tweets-extractor engine

Chatbot

Algorithms (NLP, text mining, deep learning)

Methodology

Open Research

Creation of a virtual community to work on diabetes

Increase transparency & reproducible research

Open access publications



**Better understand
diabetes in the
“real world”**

**Improve diabetes
awareness**

**Detect weak signals
in big data**

**Generate new
research questions**

In short

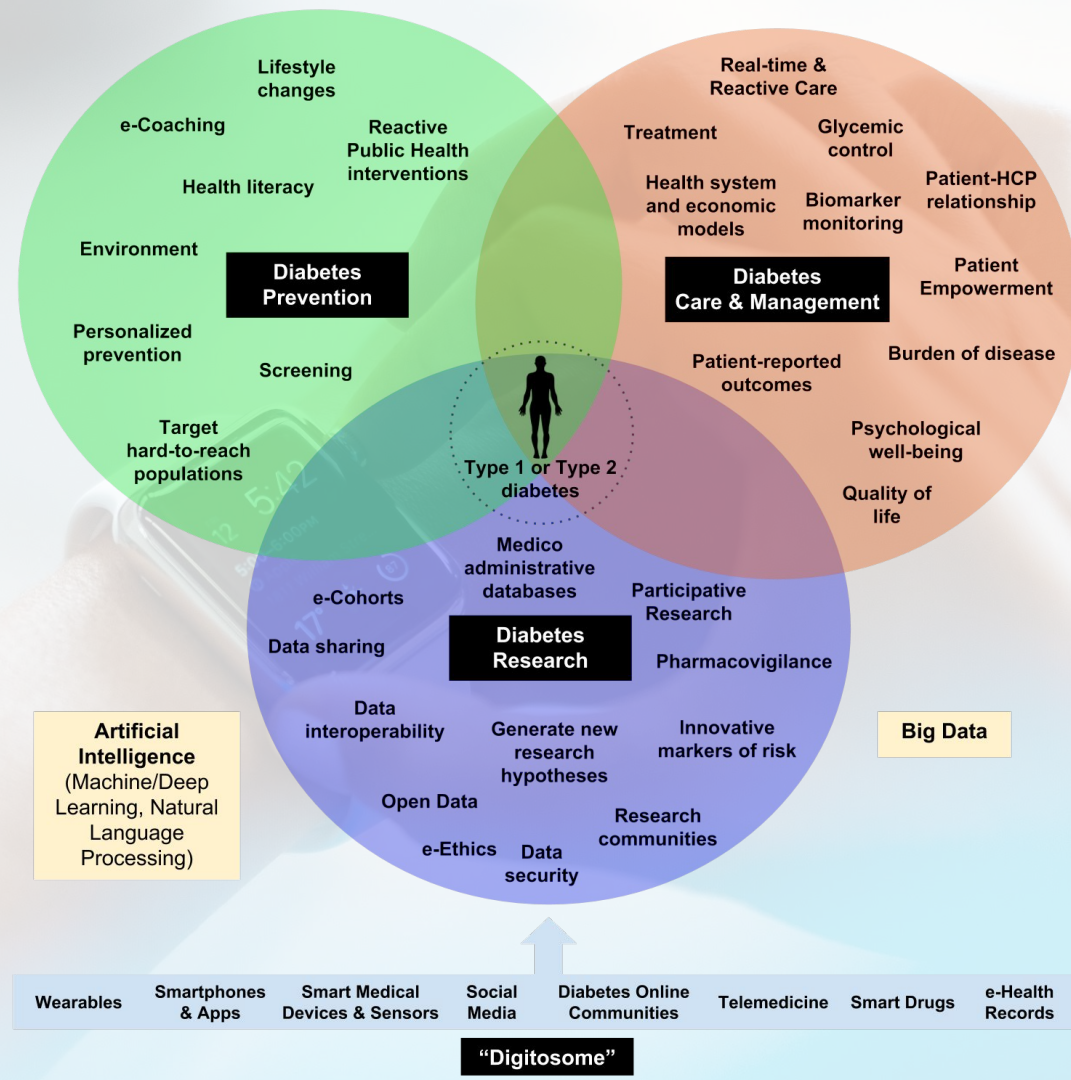
**A worldwide
project on
diabetes**

**An
unprecedented
resource**

**At the cutting
edge of
technology**

And now what ?

Impact of AI and digitosome on chronic diseases



Digital diabetes: perspectives for diabetes prevention, management and research.
Fagherazzi et al. ([Diabetes & Metabolism](#), 2018) - Open Access

Let's do better!

Need of dataviz tools and user-friendly solutions

Key for patients and HCP to use innovative solutions

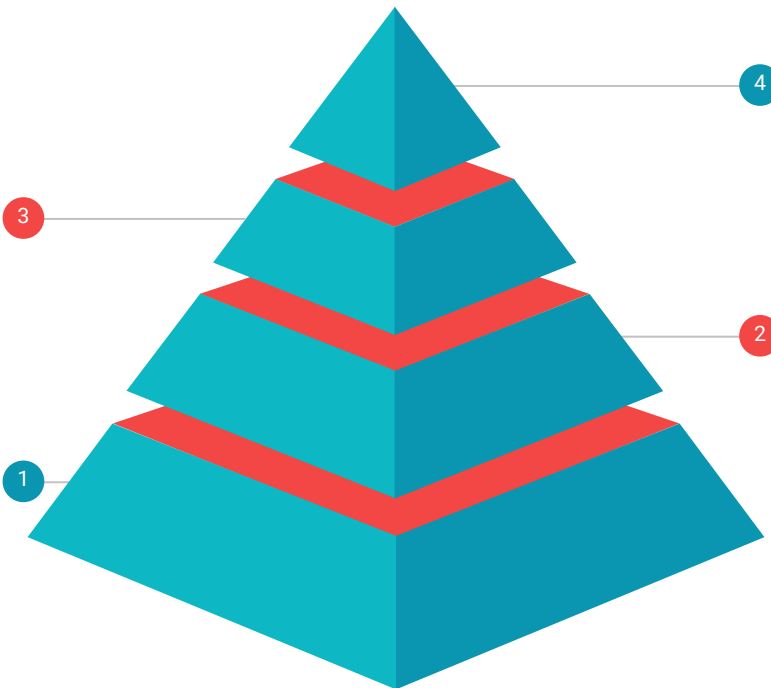
Do not increase the digital barrier and socioeconomic inequalities

Improve **UX/UI** to optimize long-term use

Patients/Participants available for research are a scarce resource

Unlikely that a given individual participates to several long term initiatives simultaneously

But we need large population sizes + long follow-up + variability



Promote Open Data/Open Source

4 Share algorithms

Definition of **new business models**, for both academics and private sectors (from based on **proprietary data** to based on **services and know-how**)

Ensure **reproducibility**

2 Be careful with isolated projects

Do not contribute to the creation of **data in silo with poor interoperability**

Include participants/patients from scratch

Actors

Governments
/ Agencies

Academics

Hospitals

Pharmas

GAFAM /
BATX

Startups

Patients /
Citizens

Disciplines

Medicine

Public
Health

Technology

Data
Science / AI

Medical
informatics

Psychology

Social
Science

Modern
epidemiology

Alternate & combine

Data driven approaches
with Hypothesis driven
research

Soft skills

+++

Communication
Teamwork
Adaptability
Problem-Solving
Creativity
Work Ethic
Interpersonal Skills
Time Management
Leadership
Attention to Detail

My message for
future epi or PH
experts

**Be at the
interface!**



MERCI ;-)

Guy Fagherazzi

guy.fagherazzi@gmail.com

Twitter : [@GFaghe](https://twitter.com/GFaghe)

