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Personal Health Technology – Opportunities & Challenges

Jakob E. Bardram
director, professor, MSc, PhD

Professor in computer science
Technical University of Denmark

Adjunct professor in public health
University of Copenhagen

Technical University of Denmark DTU · REGION H The Capital Region of Denmark · CITY OF COPENHAGEN · UNIVERSITY OF COPENHAGEN

Key figures

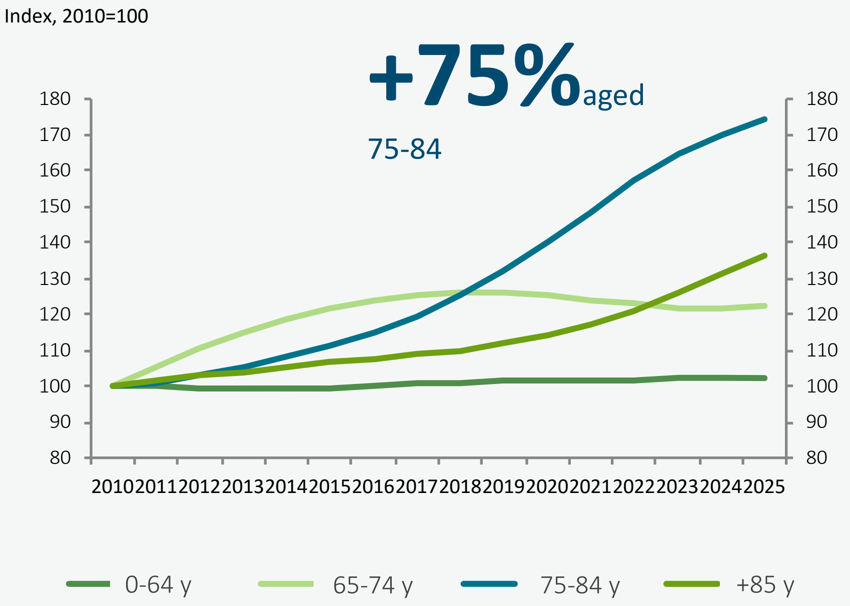
A change in our demography

The population is getting older

In 2025 the number of citizens aged 0-64 will be the same as in 2010.

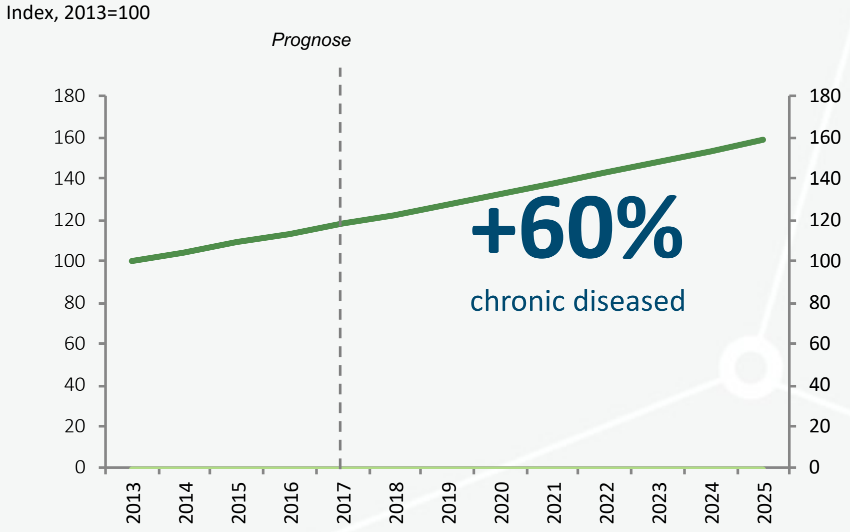
- but the number of citizens aged 75-84 will have increased by 75 percent.

→ Less tax payers and fewer health care workers



- and more people will suffer from chronic diseases

From 2013 to 2025 the number of citizens living with the most common chronic diseases is expected to increase by 60 pct.



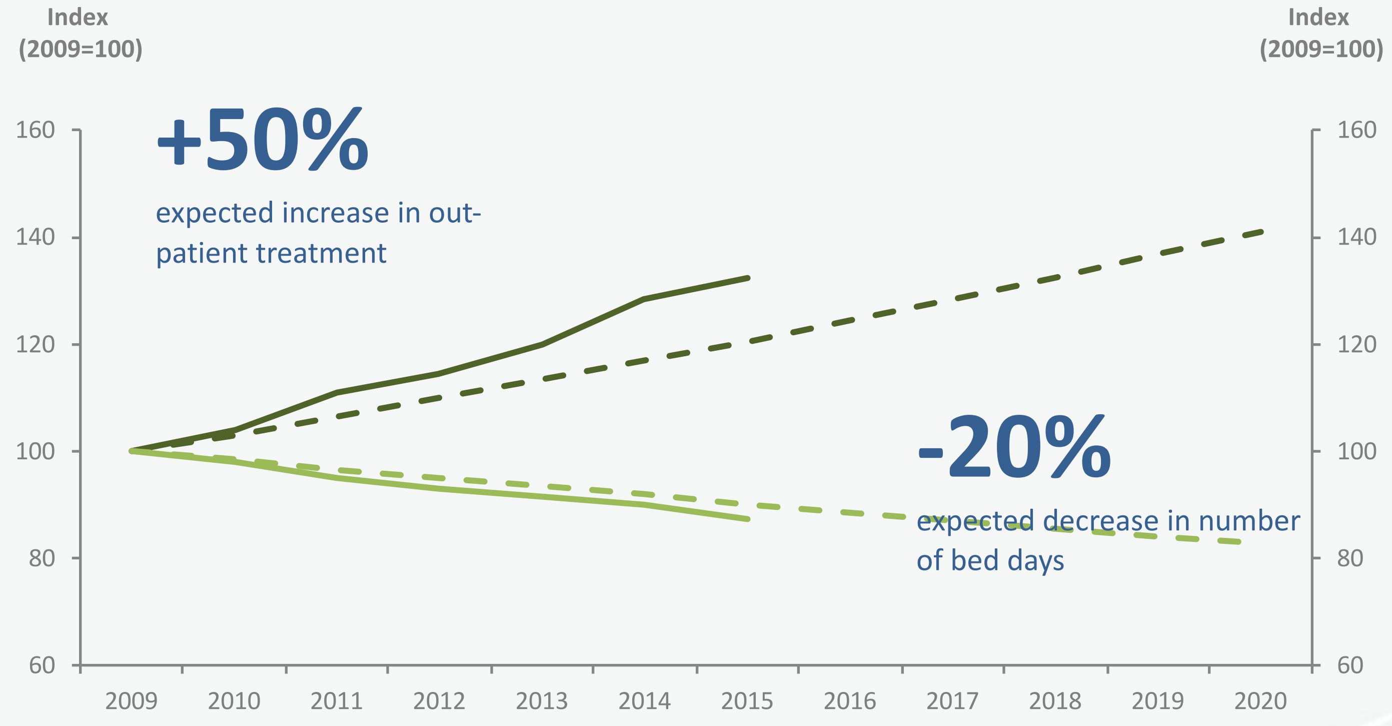
Source: Digital Health Strategy 2018-2022, Danish Ministry of Health, 2018.

A change in our structuring of hospitals

Source: Digital Health Strategy 2018-2022, Danish Ministry of Health, 2018.

Key numbers

A change in hospitalisation and technology

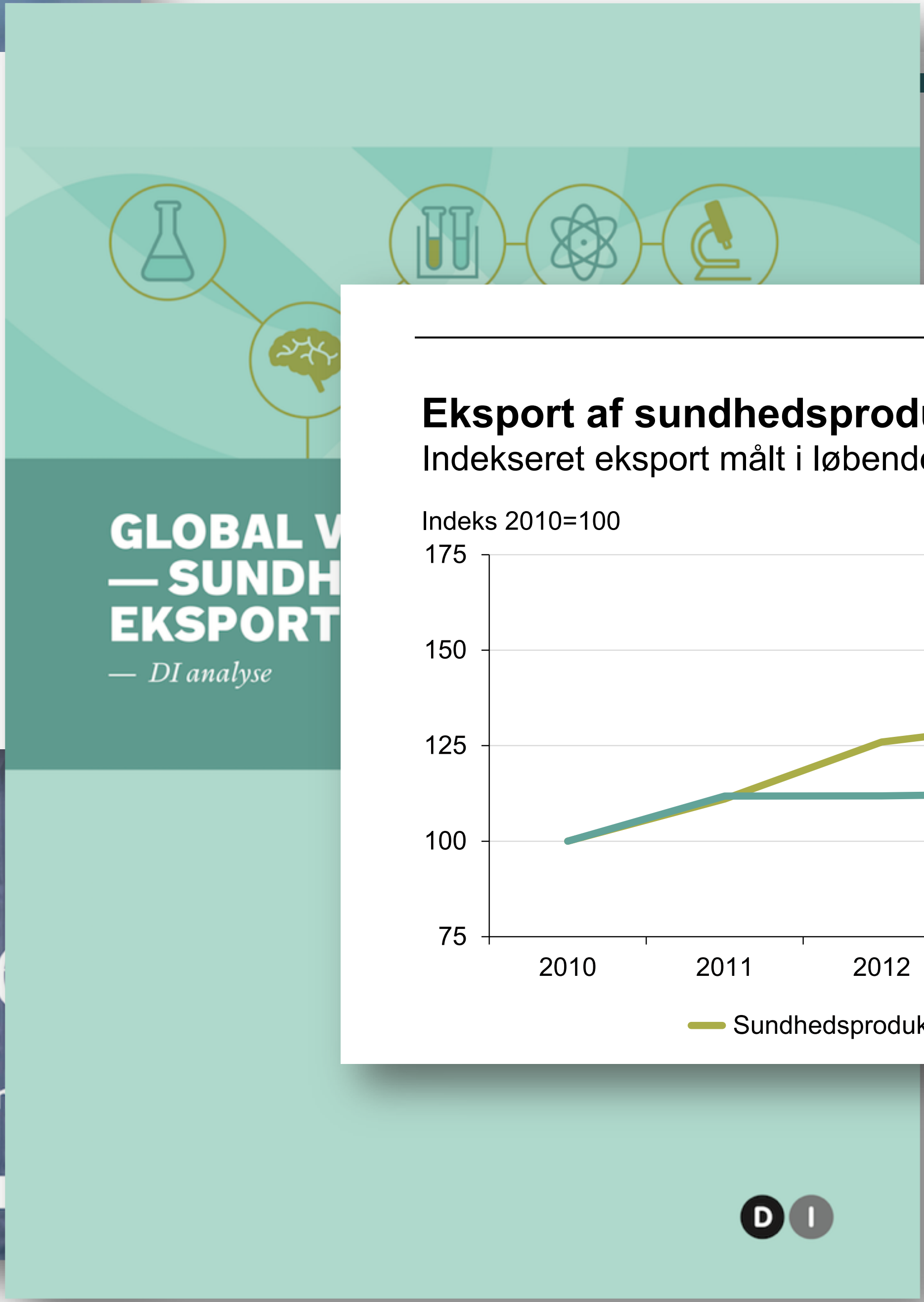


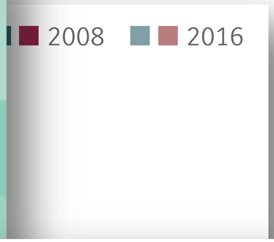
Source: Digital Health Strategy 2018-2022, Danish Ministry of Health, 2018.

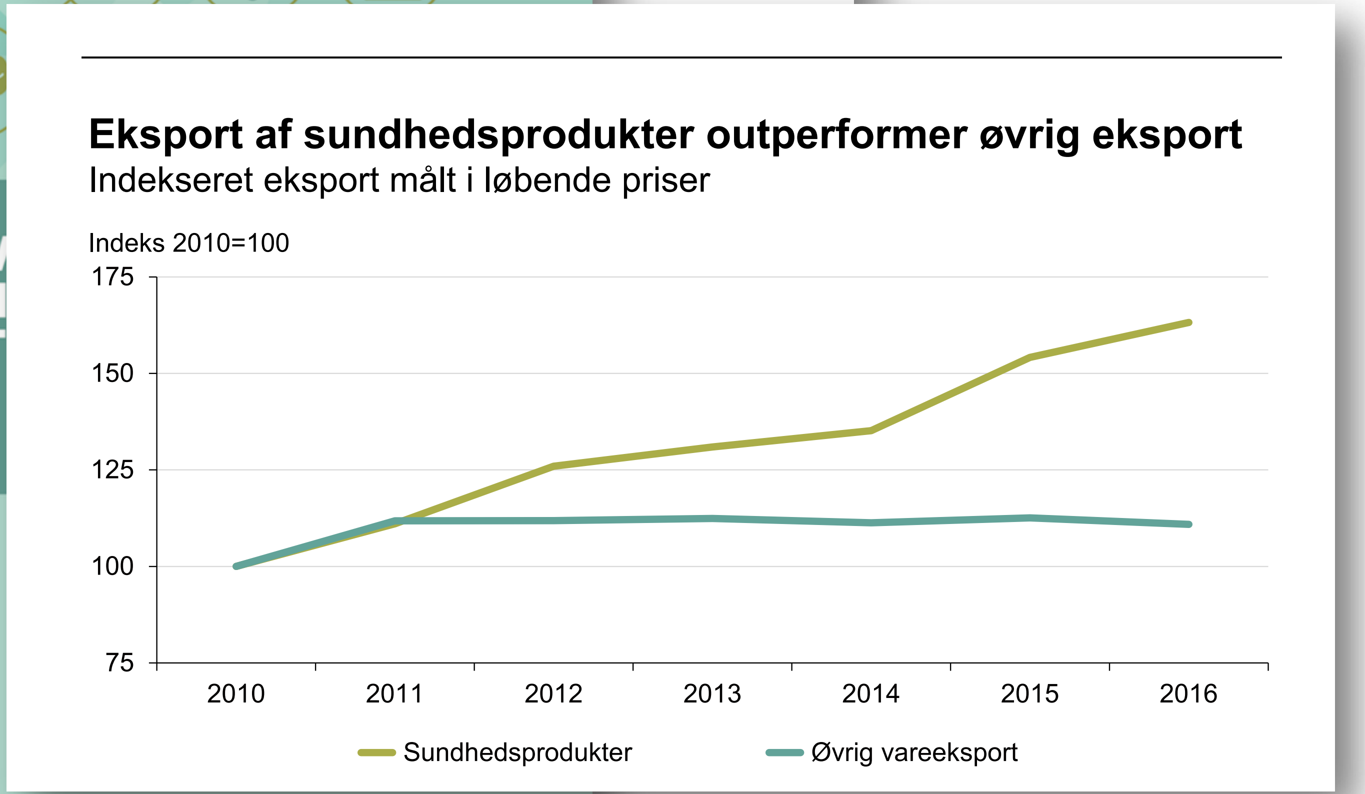
There is no real alternative to increased digital cooperation

- The percentage of elderly people will increase
- More people will live with a chronic disease
- Fewer, larger and more specialised hospitals
- Patient pathways will be faster
- More treatment will take place in the patient's home

Source: Digital Health Strategy 2018-2022, Danish Ministry of Health, 2018.







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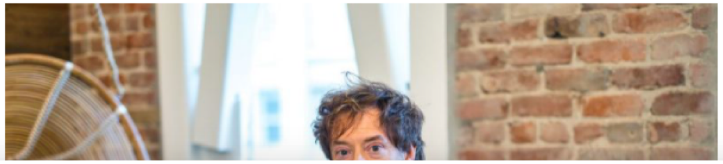
INSIGHTS

Digit
New

Digit
Fundi

Global venture capital (VC) funding in digital health, including private equity and corporate VC was just under $10 billion in 2018. This sets a new record, as investor appetite is not showin signs of waning.

This meditation app is now worth $250 million and has Trump-related stress to tha



Ari Levy
CNBC 26 March 2018

Diabetes platform mySugr exits to Roche for as much as $100M

Mike Butcher @mikebutcher / Jul 7, 2017

Comment

mySugr, a popular digital diabetes management platform which emerged from Austria a few years ago, has been acquired by health giant Roche. It now becomes the heart of Roche Diabetes Care's new patient-centered

Healthcare Challenges

Chronic diseases management
Accounting for 2/3 of all healthcare spend worldwide – and increasing – chronic disease management is and will be the main focus of health.

Preventive and predictive health
Obesity, lack of physical activity and unhealthy lifestyle are the major factors for health problems and needs to be addressed early

Regulatory
Legal and regulatory demands for protecting patient privacy, data, and safety will be enforced heavily as digital and personalized health emerge

Evidence & outcome-based health
New business models both for suppliers and vendors will be tied to clinical evidence and real-world patient outcome (efficiency)

Technology Opportunities

Personalized technology
Engaging, patient-centric, and participatory technology can deliver interventions tailored to the individual and sustain engagement “beyond-the-pill” outside traditional care settings.

Digitalization
The ubiquity of digital health and communication technology drive new models for virtual and semi-automated doctor-patient contact.

Health IoT
Pervasive, mobile and wearable technology for sensing and engaging with patients create a unique platform for personalized health delivery

Big data analytics
Computing power and advanced analytics and learning algorithms drive insight and prediction of patient behavior, treatment, and care costs


PERSONAL HEALTH
TECHNOLOGY

Personal Health Technology

Personal Medical Devices
- Hearing aids
- Diabetes, drug delivery, glucose mon.
- Respiratory
- EKG, EEG, .. monitoring
- Pacemaker

Telemedicine
- Telemedicine platforms
- Ambient Assisted Living
- CGM / Pumps

Mobile Health Technology (mHealth)
- Intel Mobile Sensing Platform
- UbifitGarden
- BeWell
- Mobilize!
- MONARCA

Fitness / Wellness Tech
- GPS & pulse
- Activity Trackers
- Smartphone apps
- Smart Watches
- Smart Devices (scales, ...)

1990 2000 2010

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Definition of Personal Health Technology

- Two broad categories
  - Professional Medical Devices
    - targeted a specific disease / health
    - 'prescribed' by doctors => customer == clinicians
    - strongly regulated – CE marked | FDA approved
  - Wellness and Consumer Health Technologies
    - targeted general wellness and wellbeing (but also for specific diseases)
    - 'consumed' by end-users => customer == consumers
    - not regulated (CE | FDA)
- … but the lines are *blurring*

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Withings

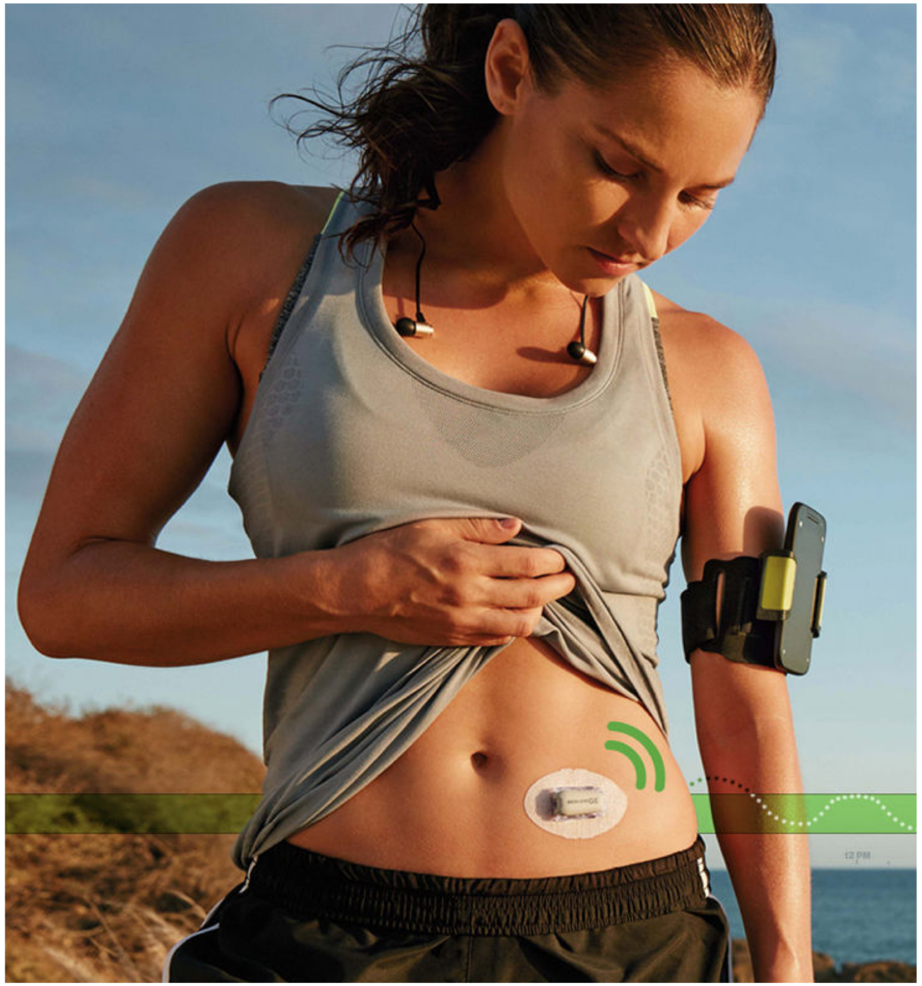
ONE DROP

One Drop

- glucose monitor (strip based)
- 24/7 expert support
- mobile/watch apps

Dexcom G6 CGM

- Continuous Glucose Monitoring (CGM)
- SmartPhone / SmartWatch
- Alerts
- Sharing



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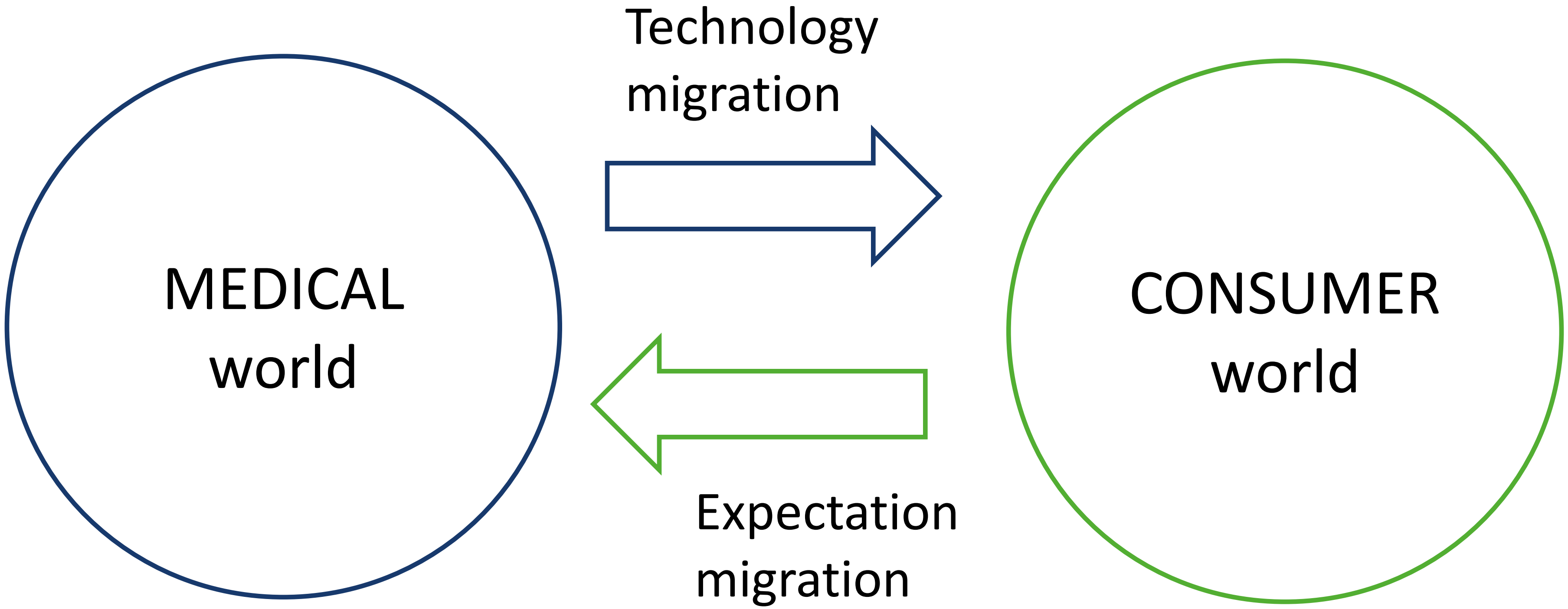
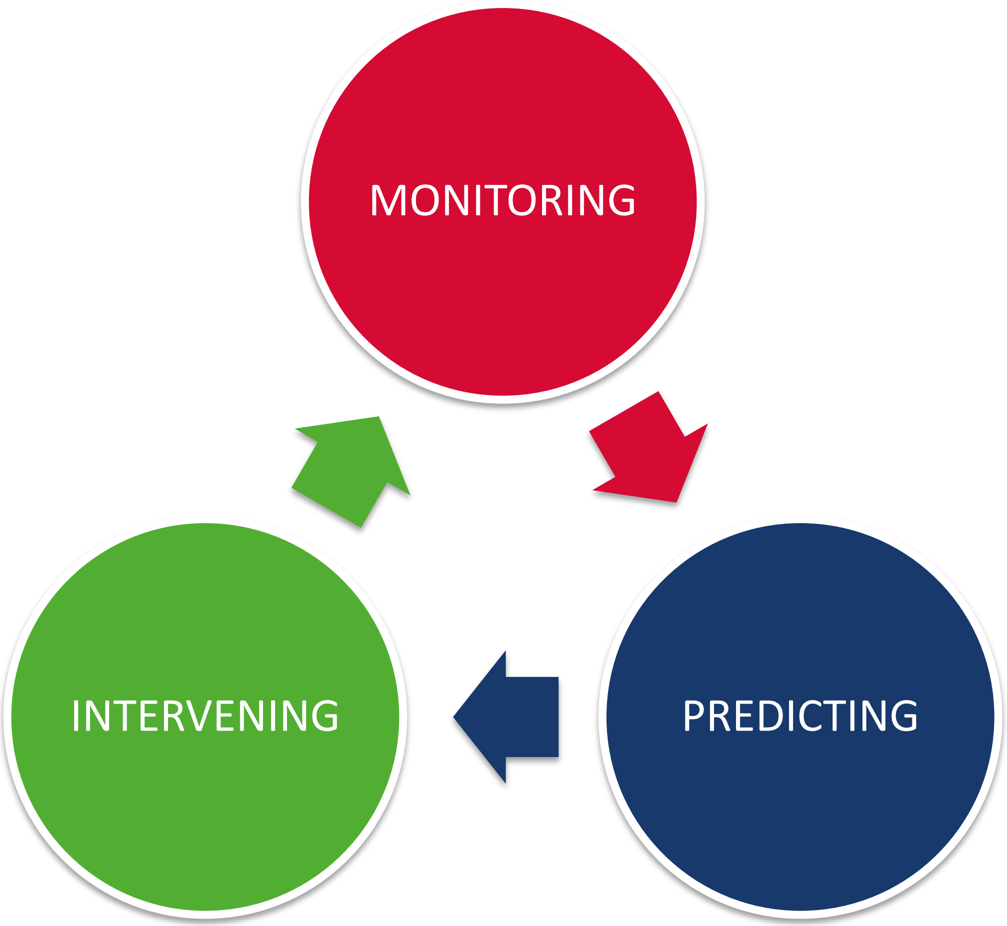

Technology
migration
MEDICAL
world
CONSUMER
world
Expectation
migration


RESEARCH

Personal Health Technology



- Psychiatry
  - depression
  - bipolar disorder
- Cardiovascular diseases
  - atrial fibrillation
- Diabetes
  - type 2

JE Bardram & M Frost. The Personal Health Technology Design Space. IEEE Pervasive Computing 15(2), 70-78, IEEE, 2016

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Personal Health Technology

- MONITORING
  - health progression & regression
  - behavior
  - context
  - longitudinal & continuously

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MONARCA

- Bipolar disorder (manio-depressive)

- MONARCA system
  - Self-assessment
    - mood | sleep | stress | medicine | …
  - Auto-assessment
    - physical activity | mobility | social activity | phone usage
  - Feedback
    - visualizations | medication | actions-to-take | triggers | early-warning-signs | impact factors
  - Mood forecast
    - predict mood for next 5 days

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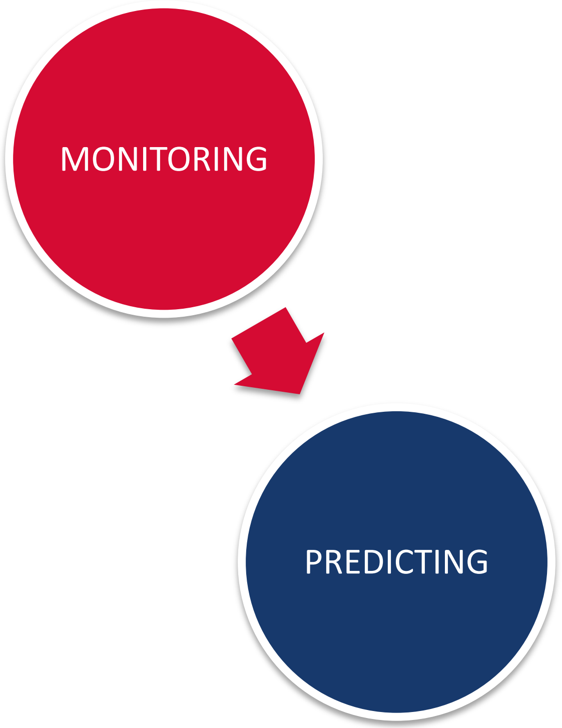
  - pattern recognition
  - correlation analysis
  - disease forecasting
  - clinical alerts & decision-support



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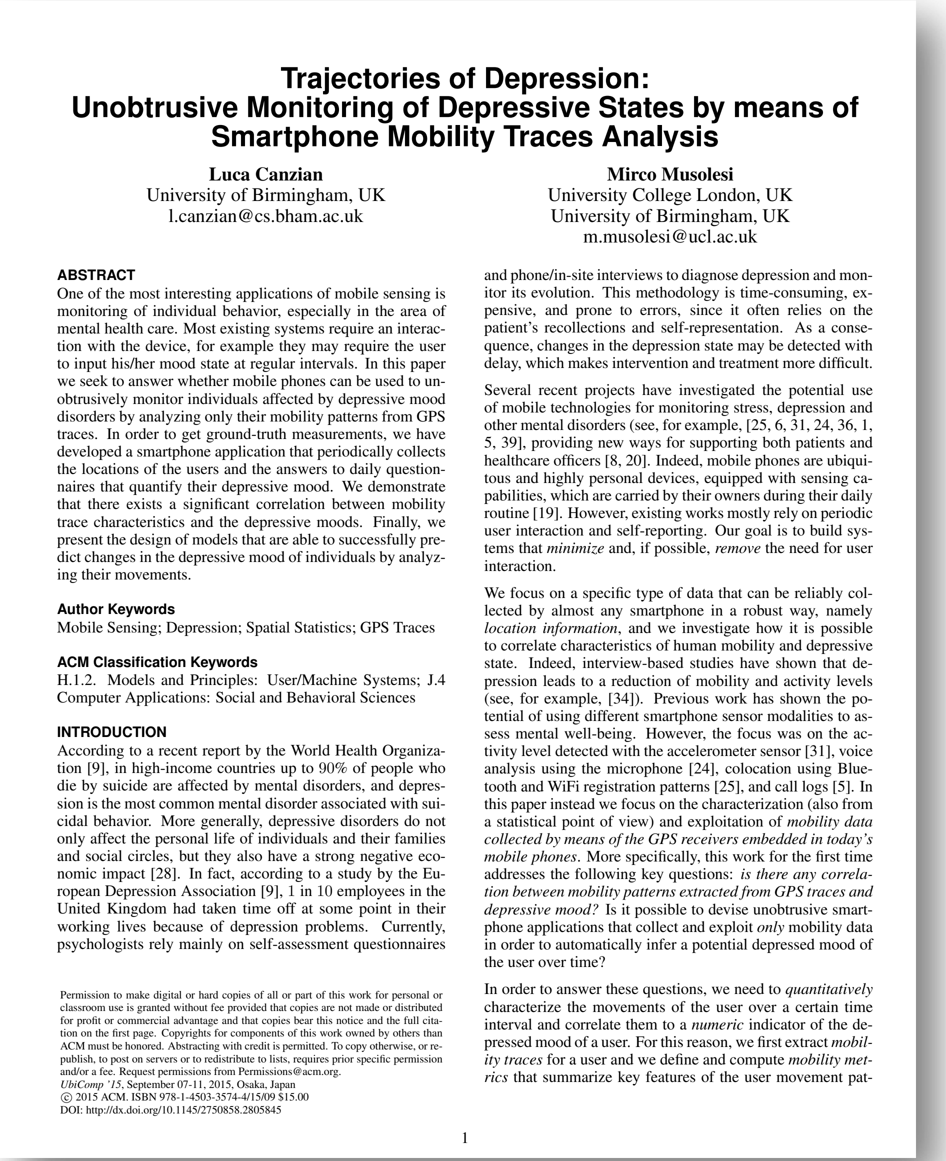
Mobility & Depression

- “significant **correlation** between mobility trace characteristics and depressive moods”
- “possible to develop **inference** algorithms for unobtrusive monitoring and prediction of depressive mood disorders”



Trajectories of Depression: Unobtrusive Monitoring of Depressive States by means of Smartphone Mobility Traces Analysis

Luca Canzian
University of Birmingham, UK
l.canzian@cs.bham.ac.uk

Mirco Musolesi
University College London, UK
University of Birmingham, UK
m.musolesi@ucl.ac.uk

ABSTRACT

One of the most interesting applications of mobile sensing is monitoring of individual behavior, especially in the area of mental health care. Most existing systems require an interaction with the device, for example they may require the user to input his/her mood state at regular intervals. In this paper we seek to answer whether mobile phones can be used to unobtrusively monitor individuals affected by depressive mood disorders by analyzing only their mobility patterns from GPS traces. In order to get ground-truth measurements, we have developed a smartphone application that periodically collects the locations of the users and the answers to daily questionnaires that quantify their depressive mood. We demonstrate that there exists a significant correlation between mobility trace characteristics and the depressive moods. Finally, we present the design of models that are able to successfully predict changes in the depressive mood of individuals by analyzing their movements.

Author Keywords

Mobile Sensing; Depression; Spatial Statistics; GPS Traces

ACM Classification Keywords

H.1.2. Models and Principles: User/Machine Systems; J.4 Computer Applications: Social and Behavioral Sciences

INTRODUCTION

According to a recent report by the World Health Organization [9], in high-income countries up to 90% of people who die by suicide are affected by mental disorders, and depression is the most common mental disorder associated with suicidal behavior. More generally, depressive disorders do not only affect the personal life of individuals and their families and social circles, but they also have a strong negative economic impact [28]. In fact, according to a study by the European Depression Association [9], 1 in 10 employees in the United Kingdom had taken time off at some point in their working lives because of depression problems. Currently, psychologists rely mainly on self-assessment questionnaires and phone/in-site interviews to diagnose depression and monitor its evolution. This methodology is time-consuming, expensive, and prone to errors, since it often relies on the patient's recollections and self-representation. As a consequence, changes in the depression state may be detected with delay, which makes intervention and treatment more difficult.

Several recent projects have investigated the potential use of mobile technologies for monitoring stress, depression and other mental disorders (see, for example, [25, 6, 31, 24, 36, 1, 5, 39], providing new ways for supporting both patients and healthcare officers [8, 20]. Indeed, mobile phones are ubiquitous and highly personal devices, equipped with sensing capabilities, which are carried by their owners during their daily routine [19]. However, existing works mostly rely on periodic user interaction and self-reporting. Our goal is to build systems that *minimize* and, if possible, *remove* the need for user interaction.

We focus on a specific type of data that can be reliably collected by almost any smartphone in a robust way, namely *location information*, and we investigate how it is possible to correlate characteristics of human mobility and depressive state. Indeed, interview-based studies have shown that depression leads to a reduction of mobility and activity levels (see, for example, [34]). Previous work has shown the potential of using different smartphone sensor modalities to assess mental well-being. However, the focus was on the activity level detected with the accelerometer sensor [31], voice analysis using the microphone [24], colocation using Bluetooth and WiFi registration patterns [25], and call logs [5]. In this paper instead we focus on the characterization (also from a statistical point of view) and exploitation of *mobility data collected by means of the GPS receivers embedded in today's mobile phones*. More specifically, this work for the first time addresses the following key questions: *is there any correlation between mobility patterns extracted from GPS traces and depressive mood?* Is it possible to devise unobtrusive smartphone applications that collect and exploit *only* mobility data in order to automatically infer a potential depressed mood of the user over time?

In order to answer these questions, we need to *quantitatively* characterize the movements of the user over a certain time interval and correlate them to a *numeric* indicator of the depressed mood of a user. For this reason, we first extract *mobility traces* for a user and we define and compute *mobility metrics* that summarize key features of the user movement pat-

UbiComp '15, September 07-11, 2015, Osaka, Japan

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Canzian L, Musolesi M. Trajectories of Depression: Unobtrusive Monitoring of Depressive States by means of Smartphone Mobility Traces Analysis. In: *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (ACM UbiComp'15)*. ACM; 2015.

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Voice & Mood

Collection of voice features in naturalistic setting

- N=28 | 12 week
- HDRS-17 (depre
- 179 clinical ratir
- openSMILE (em

Classification resu
(s.d.)

- depressive state : 70% (0.13)
- manic state : 61% (0.04)

Classification accuracy were not significantly increased when combining voice features with automatically generated objective data

"Voice features collected in naturalistic settings using smartphones may be used as objective state markers in patients with bipolar disorder. "

OPEN

Citation: Transl Psychiatry (2016) **6**, e856; doi:10.1038/tp.2016.123

www.nature.com/tp

ORIGINAL ARTICLE

Voice analysis as an objective state marker in bipolar disorder

M Faurholt-Jepsen[1], J Busk[2], M Frost[3], M Vinberg[1], EM Christensen[1], O Winther[2], JE Bardram[2] and LV Kessing[1]

Changes in speech have been suggested as sensitive and valid measures of depression and mania in bipolar disorder. The present study aimed at investigating (1) voice features collected during phone calls as objective markers of affective states in bipolar disorder and (2) if combining voice features with automatically generated objective smartphone data on behavioral activities (for example, number of text messages and phone calls per day) and electronic self-monitored data (mood) on illness activity would increase the accuracy as a marker of affective states. Using smartphones, voice features, automatically generated objective

6; doi:10.1038/tp.2016.123; published online 19 July 2016

monitoring and collection of real-time data on depressive and manic symptoms outside clinical settings between outpatient visits.

Studies analyzing the spoken language in affective disorders date back as early as 1938.[5] A number of clinical observations suggest that reduced speech activity and changes in voice features such as pitch may be sensitive and valid measures of prodromal symptoms of depression and effect of treatment.[6–12] Conversely, it has been suggested that increased speech activity may predict a switch to hypomania.[13] Item number eight on the HAMD (psychomotor retardation) and item number six on the YMRS (speech amount and rate) are both related to changes in speech, illustrating that factors related to speech activity are important aspects to evaluate in the assessment of symptoms' severity in bipolar disorder. Based on these clinical observations there is an increasing interest in electronic systems for speech emotion recognition that can be used to extract useful semantics from speech and thereby provide information on the emotional state of the speaker (for example, information on pitch of the voice).[14]

Software for ecologically extracting data on multiple voice features during phone calls made in naturalistic settings over prolonged time-periods has been developed[15] and a few preliminary studies have been published.[16–20] One study extracted voice features in six patients with bipolar disorder type I using software on smartphones and demonstrated that changes in speech data were able to detect the presence of depressive and hypomanic symptoms assessed with weekly phone-based clinicians administrated ratings using the HAMD and the YMRS, respectively.[17] However, none of the patients in the study presented with manic symptoms during the study period, and the clinical assessments were phone-based. Another study on six patients with bipolar disorder showed that combining statistics on objectively collected duration of phone calls per day and extracted voice features on variance of pitch increased the accuracy of classification of affective states compared with solely using variance of pitch for classification.[18,19] The study did not state if and how the affective states were assessed during the monitoring period.

In addition to voice features, changes in behavioral activities such as physical activity/psychomotor activity[21–24] and the level of engagement in social activities[25] represent central aspects of

[1]Psychiatric Center Copenhagen, Rigshospitalet, Copenhagen, Denmark; [2]DTU Compute, Technical University of Denmark (DTU), Lyngby, Denmark and [3]The Pervasive Interaction Laboratory, IT University of Copenhagen, Copenhagen, Denmark. Correspondence: Dr M Faurholt-Jepsen, Psychiatric Center Copenhagen, Rigshospitalet, Blegdamsvej 9, DK-2100 Copenhagen, Denmark.
E-mail: maria@faurholt-jepsen.dk
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  - behavior
  - context
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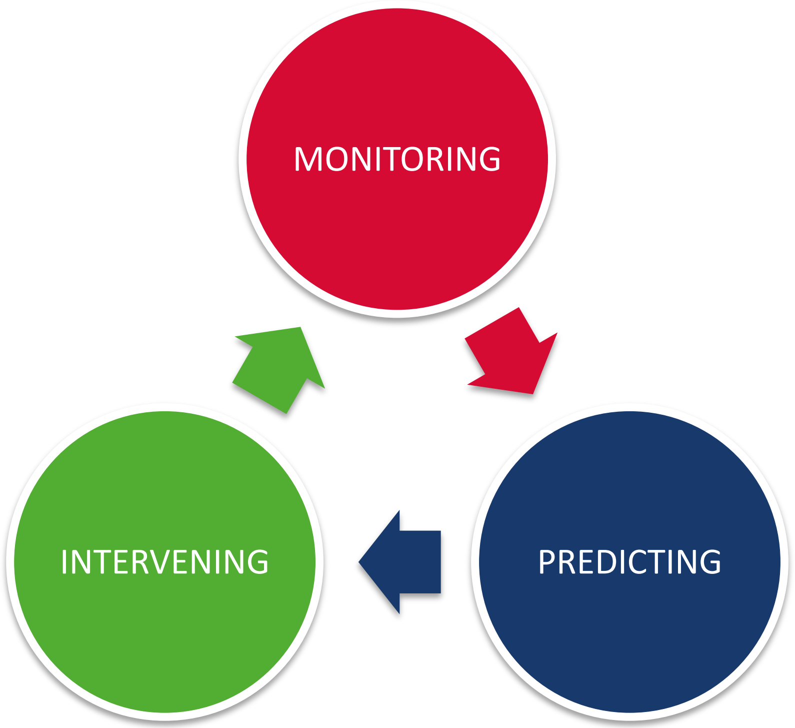
  - disease forecasting
  - clinical alerts & decision-support
- INTERVENTION
  - early detection
  - context-aware feedback & treatment
  - clinical intervention & prescription



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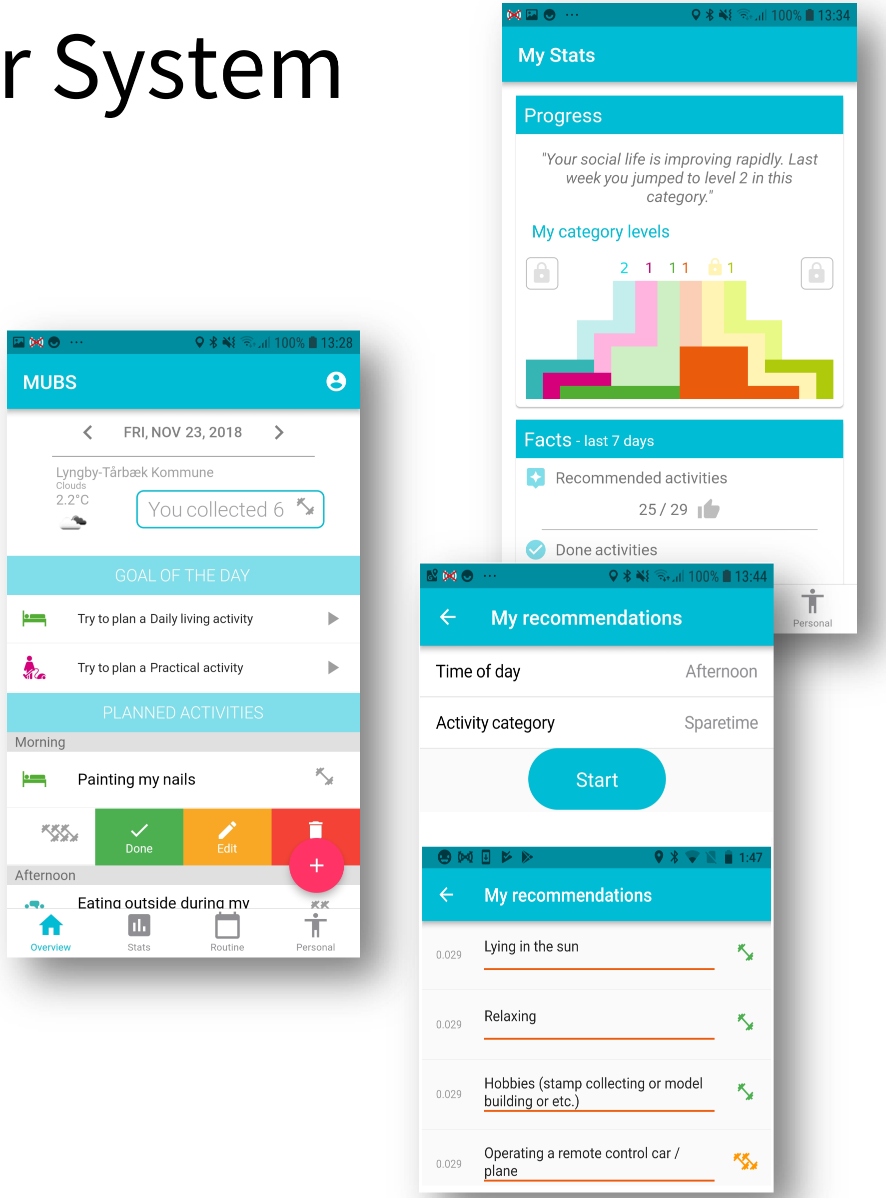
MUBS: A Näive Bayes Recommender System for Behavioral Activation

- Behavioral Activation (BA)
  - Activating patients to do more activities in six core categories

- Daily activity recommendation
  - just-in-time adaptive intervention

$$P(C_j|n_y) = \frac{P(C_j)\prod_{t=1}^{T}\sum_{i=1}^{|d_t|}P(w_{ti}|C_jT_t)}{P(n_y)}$$

- Features
  - activity, difficulty, category
  - time, day, weather, location, physical activity



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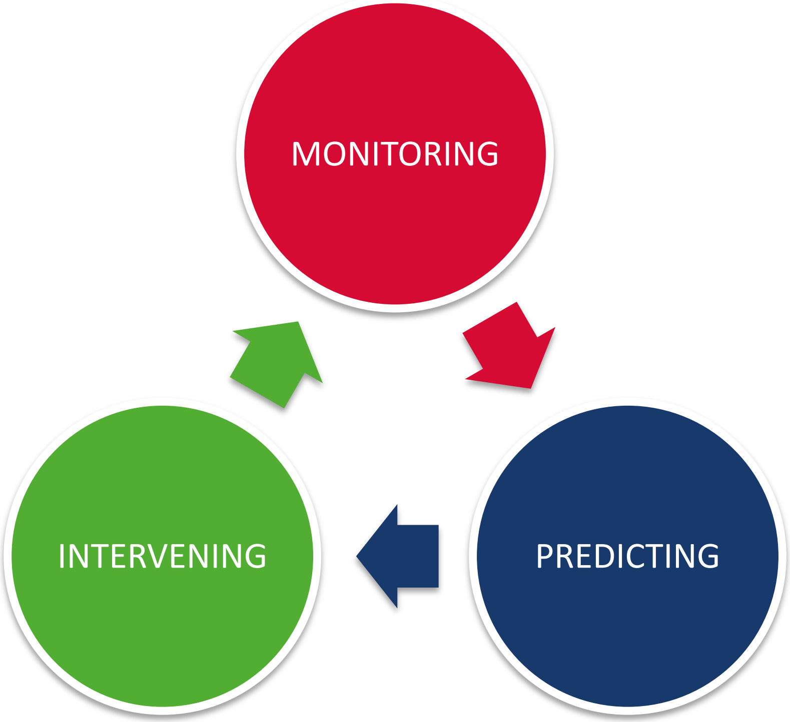

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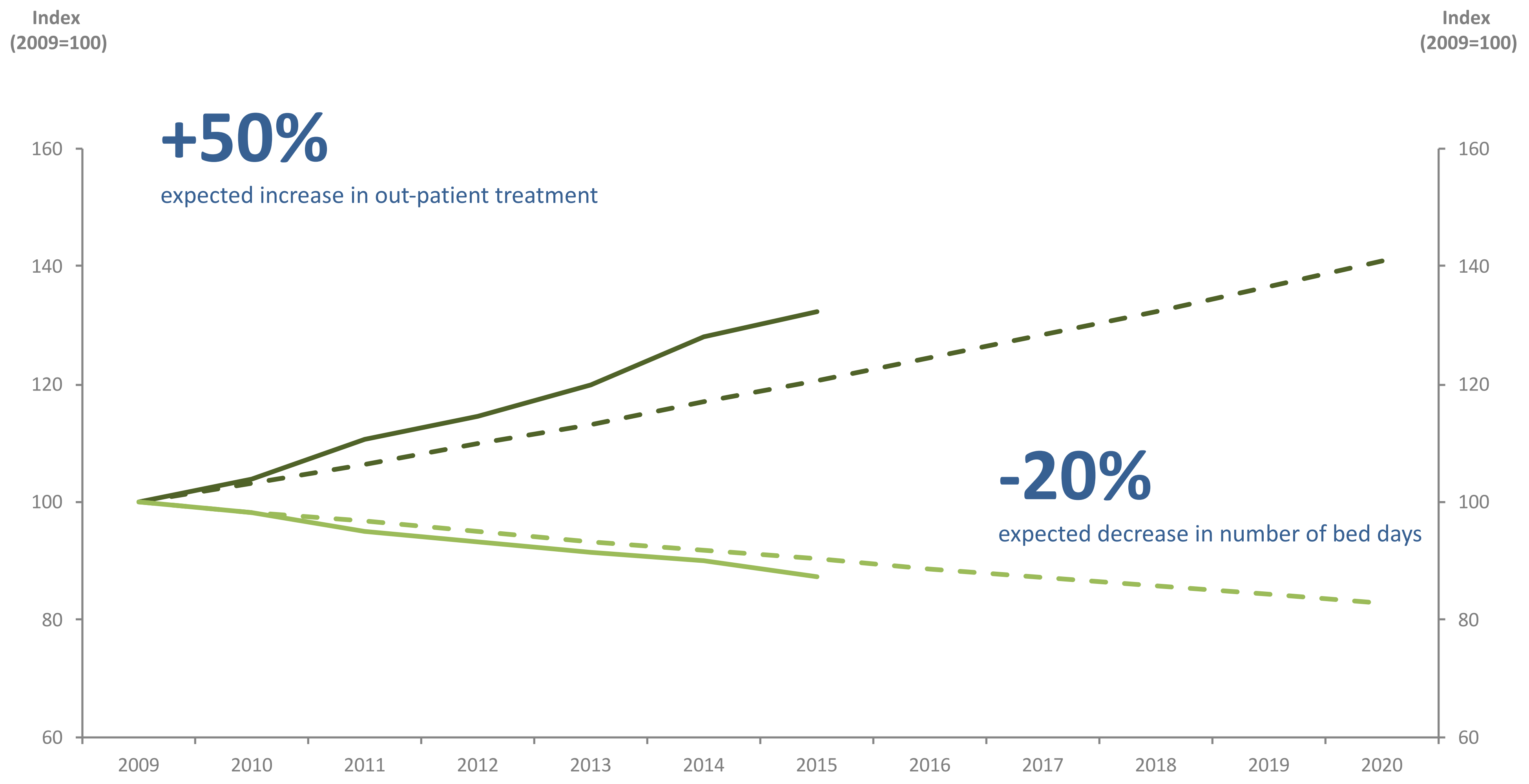

Source: Digital Health Strategy 2018-2022, Danish Ministry of Health, 2018.

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4P Healthcare Technology

Preventive
- avoid (chronic) health problems in the first place

Predictive
- catch health problems early

Participatory
- engage people in their own health

Personalized
- tailor treatment to the individual ("personalized medicine")

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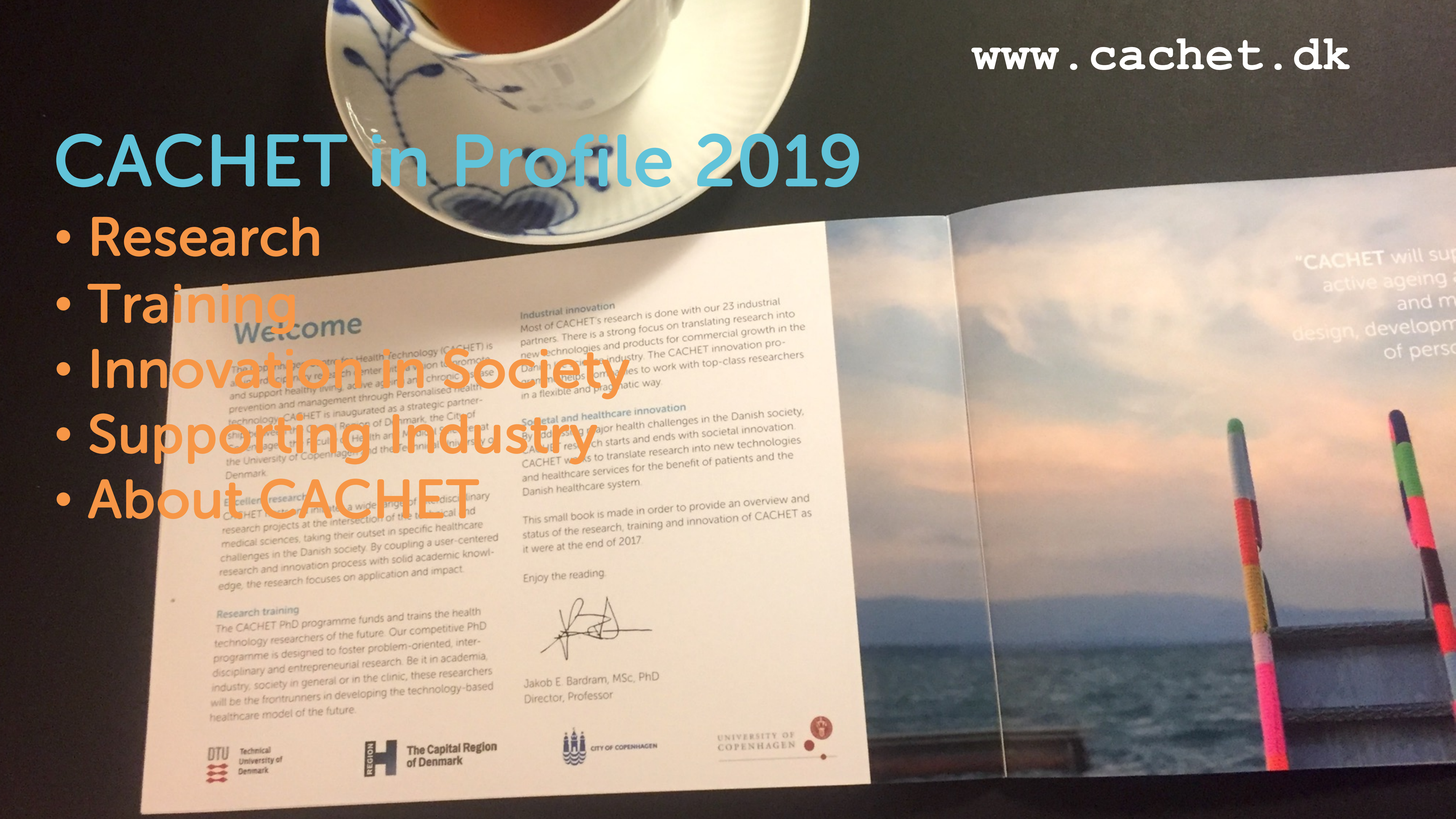

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