Technical University of Denmark

10+ YEARS OF AI IN MENTAL HEALTH

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A All ages

Leading causes 1990	Percentage of DALYs 1990	Leading causes 2019	Percentage of DALYs 2019	Percentage change in number of DALYs, 1990–2019	Percentage change in age-standardised DALY rate, 1990–2019
1 Neonatal disorders	10·6 (9·9 to 11·4)	1 Neonatal disorders	7·3 (6·4 to 8·4)	−32·3 (−41·7 to −20·8)	−32·6 (−42·1 to −21·2)
2 Lower respiratory infections	8·7 (7·6 to 10·0)	2 Ischaemic heart disease	7·2 (6·5 to 7·9)	50·4 (39·9 to 60·2)	−28·6 (−33·3 to −24·2)
3 Diarrhoeal diseases	7·3 (5·9 to 8·8)	3 Stroke	5·7 (5·1 to 6·2)	32·4 (22·0 to 42·2)	−35·2 (−40·5 to −30·5)
4 Ischaemic heart disease	4·7 (4·4 to 5·0)	4 Lower respiratory infections	3·8 (3·3 to 4·3)	−56·7 (−64·2 to −47·5)	−62·5 (−69·0 to −54·9)
5 Stroke	4·2 (3·9 to 4·5)	5 Diarrhoeal diseases	3·2 (2·6 to 4·0)	−57·5 (−66·2 to −44·7)	−64·6 (−71
6 Congenital birth defects	3·2 (2·3 to 4·8)	6 COPD	2·9 (2·6 to 3·2)	25·6 (15·1 to 46·0)	−39·8 (−4
7 Tuberculosis	3·1 (2·8 to 3·4)	7 Road injuries	2·9 (2·6 to 3·0)	2·4 (−6·9 to 10·8)	−31·0 (−37
8 Road injuries	2·7 (2·6 to 3·0)	8 Diabetes	2·8 (2·5 to 3·1)	147·9 (135·9 to 158·9)	24·4 (18
9 Measles	2·7 (0·9 to 5·6)	9 Low back pain	2·5 (1·9 to 3·1)	46·9 (43·3 to 50·5)	−16·3 (−17
10 Malaria	2·5 (1·4 to 4·1)	10 Congenital birth defects	2·1 (1·7 to 2·6)	−37·3 (−50·6 to −12·8)	−40·0 (−52
11 COPD	2·3 (1·9 to 2·5)	11 HIV/AIDS	1·9 (1·6 to 2·2)	127·7 (97·3 to 171·7)	58·5 (37
12 Protein-energy malnutrition	2·0 (1·6 to 2·7)	12 Tuberculosis	1·9 (1·7 to 2·0)	−41·0 (−47·2 to −33·5)	−62·8 (−6
13 Low back pain	1·7 (1·2 to 2·1)	13 Depressive disorders	1·8 (1·4 to 2·4)	61·1 (56·9 to 65·0)	−1·8 (−2
14 Self-harm	1·4 (1·2 to 1·5)	14 Malaria	1·8 (0·9 to 3·1)	−29·4 (−56·9 to 6·6)	−37·8 (−6
15 Cirrhosis	1·3 (1·2 to 1·5)	15 Headache disorders	1·8 (0·4 to 3·8)	56·7 (52·4 to 62·1)	1·1 (−4
16 Meningitis	1·3 (1·1 to 1·5)	16 Cirrhosis	1·8 (1·6 to 2·0)	33·0 (22·4 to 48·2)	−26·8 (−32
17 Drowning	1·3 (1·1 to 1·4)	17 Lung cancer	1·8 (1·6 to 2·0)	69·1 (53·1 to 85·4)	−16·2 (−24
18 Headache disorders	1·1 (0·2 to 2·4)	18 Chronic kidney disease	1·6 (1·5 to 1·8)	93·2 (81·6 to 105·0)	6·3 (0·2
19 Depressive disorders	1·1 (0·8 to 1·5)	19 Other musculoskeletal	1·6 (1·2 to 2·1)	128·9 (122·0 to 136·3)	30·7 (27·
20 Diabetes	1·1 (1·0 to 1·2)	20 Age-related hearing loss	1·6 (1·2 to 2·1)	82·8 (75·2 to 88·9)	−1·8 (−3·
21 Lung cancer	1·0 (1·0 to 1·1)	21 Falls	1·5 (1·4 to 1·7)	47·1 (31·5 to 61·0)	−14·5 (−22
22 Falls	1·0 (0·9 to 1·2)	22 Self-harm	1·3 (1·2 to 1·5)	−5·6 (−14·2 to 3·7)	−38·9 (−4
23 Dietary iron deficiency	1·0 (0·7 to 1·3)	23 Gynaecological diseases	1·3 (0·9 to 1·5)	48·7 (45·8 to 51·8)	6·8 (·8
24 Interpersonal violence	0·9 (0·9 to 1·0)	24 Anxiety disorders	1·1 (0·8 to 1·5)	53·7 (48·8 to 59·1)	−0·1 (−1
25 Whooping cough	0·9 (0·4 to 1·7)	25 Dietary iron deficiency	1·1 (0·8 to 1·5)	13·8 (10·5 to 17·2)	−16·4 (−18
27 Age-related hearing loss	0·8 (0·6 to 1·1)	26 Interpersonal violence	1·1 (1·0 to 1·2)	10·2 (3·2 to 19·2)	−23·8 (−28·6 to −17·8)
29 Chronic kidney disease	0·8 (0·8 to 0·9)	40 Meningitis	0·6 (0·5 to 0·8)	−51·3 (−59·4 to −42·0)	−57·2 (−64·4 to −48·6)
30 HIV/AIDS	0·8 (0·6 to 1·0)	41 Protein-energy malnutrition	0·6 (0·5 to 0·7)	−71·1 (−79·6 to −59·7)	−74·5 (−82·0 to −64·5)
32 Gynaecological diseases	0·8 (0·6 to 1·0)	46 Drowning	0·5 (0·5 to 0·6)	−60·6 (−65·2 to −53·6)	−68·2 (−71·9 to −62·8)
34 Anxiety disorders	0·7 (0·5 to 1·0)	55 Whooping cough	0·4 (0·2 to 0·7)	−54·5 (−74·6 to −16·9)	−56·3 (−75·6 to −20·3)
35 Other musculoskeletal	0·7 (0·5 to 1·0)	71 Measles	0·3 (0·1 to 0·6)	−89·8 (−92·3 to −86·8)	−90·4 (−92·8 to −87·5)

Global Health Metrics

Global burden of 369 diseases and injuries in 204 countries and territories, 1990–2019: a systematic analysis for the Global Burden of Disease Study 2019

*GBD 2019 Diseases and Injuries Collaborators**

Lancet 2020; 396: 1204–22
This online publication has been corrected. The corrected version first appeared at thelancet.com on October 23, 2020

*For the list of Collaborators see Viewpoint *Lancet* 2020; 396: 1135–59
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Summary

Background In an era of shifting global agendas and expanded emphasis on non-communicable diseases and injuries along with communicable diseases, sound evidence on trends by cause at the national level is essential. The Global Burden of Diseases, Injuries, and Risk Factors Study (GBD) provides a systematic scientific assessment of published, publicly available, and contributed data on incidence, prevalence, and mortality for a mutually exclusive and collectively exhaustive list of diseases and injuries.

Methods GBD estimates incidence, prevalence, mortality, years of life lost (YLLs), years lived with disability (YLDs), and disability-adjusted life-years (DALYs) due to 369 diseases and injuries, for two sexes, and for 204 countries and territories. Input data were extracted from censuses, household surveys, civil registration and vital statistics, disease registries, health service use, air pollution monitors, satellite imaging, disease notifications, and other sources. Cause-specific death rates and cause fractions were calculated using the Cause of Death Ensemble model and spatiotemporal Gaussian process regression. Cause-specific deaths were adjusted to match the total all-cause deaths calculated as part of the GBD population, fertility, and mortality estimates. Deaths were multiplied by standard life expectancy at each age to calculate YLLs. A Bayesian meta-regression modelling tool, DisMod-MR 2.1, was used to ensure consistency between incidence, prevalence, remission, excess mortality, and cause-specific mortality for most causes. Prevalence estimates were multiplied by disability weights for mutually exclusive sequelae of diseases and injuries to calculate YLDs. We considered results in the context of the Socio-demographic Index (SDI), a composite indicator of income per capita, years of schooling, and fertility rate in females younger than 25 years. Uncertainty intervals (UIs) were generated for every metric using the 25th and 975th ordered 1000 draw values of the posterior distribution.

Findings Global health has steadily improved over the past 30 years as measured by age-standardised DALY rates. After taking into account population growth and ageing, the absolute number of DALYs has remained stable. Since 2010, the pace of decline in global age-standardised DALY rates has accelerated in age groups younger than 50 years compared with the 1990–2010 time period, with the greatest annualised rate of decline occurring in the 0–9-year age group. Six infectious diseases were among the top ten causes of DALYs in children younger than 10 years in 2019: lower respiratory infections (ranked second), diarrhoeal diseases (third), malaria (fifth), meningitis (sixth), whooping cough (ninth), and sexually transmitted infections (which, in this age group, is fully accounted for by congenital syphilis; ranked tenth). In adolescents aged 10–24 years, three injury causes were among the top causes of DALYs: road injuries (ranked first), self-harm (third), and interpersonal violence (fifth). Five of the causes that were in the top ten for ages 10–24 years were also in the top ten in the 25–49-year age group: road injuries (ranked first), HIV/AIDS (second), low back pain (fourth), headache disorders (fifth), and depressive disorders (sixth). In 2019, ischaemic heart disease and stroke were the top-ranked causes of DALYs in both the 50–74-year and 75-years-and-older age groups. Since 1990, there has been a marked shift towards a greater proportion of burden due to YLDs from non-communicable diseases and injuries

2007

2009


htc
Sprint
10:08 AM
10
AM
08
Seattle
Mostly Sunny
Wed, Aug 05
69° H: 75°
L: 58°
Market
Voicemail
People
16
Mail
Browser
Camera
Phone
menu

Opportunities for UbiComp in Mental Health?

"**Continuous multimodal monitoring** is of particular importance for preventing mental disorders. A relevant example is prevention of clinical depression. An early assessment of risk factors or an early detection of negative vital signs could significantly reduce this cost through early prevention." (**2010**)

- **Core Research Topics**
  - mobile sensing
  - ecological momentary assessment
  - mood & episode prediction
  - psycho-education
  - clinical diagnosis

Special Topic – Original Articles © Schattauer 2010 67

Pervasive Healthcare

Pervasive Healthcare

Paving the Way for a Pervasive, User-centered and Preventive Healthcare Model

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Keywords
Pervasive healthcare, pervasive sensing, pervasive prevention, pervasive technology evaluation, ubiquitous computing

Summary
Objectives: The aging of the population creates pressure on the healthcare systems in various ways. A massive increase of chronic disease conditions and age-related illness are predicted as the dominant forces driving the future health care. The objective of this paper is to present future research demands in pervasive healthcare with the goal to meet the healthcare challenges by paving the way for a pervasive, user-centered and preventive healthcare model.
Methods: This paper presents recent methodological approaches and proposes future research topics in three areas: i) pervasive, continuous and reliable long-term monitoring systems; ii) prevention through pervasive technology as a key element to maintain lifelong wellness; and iii) design and evaluation methods for ubiquitous, patient-centric technologies.
Results: Pervasive technology has been identified as a strong asset for achieving the vision of user-centered preventive healthcare. In order to make this vision a reality, new strategies for design, development and evaluation of technology have to find a common denominator and consequently interoperate. Moreover, the potential of pervasive healthcare technologies offers new opportunities beyond traditional disease treatment and may play a major role in prevention, e.g. motivate healthy behavior and disease prevention throughout all stages of life. In this sense, open challenges in future research have to be addressed such as the variability of health indicators between individuals and the manner in which relevant health indicators are provided to the users in order to maximize their motivation to mitigate or prevent unhealthy behaviors. Additionally, collecting evidence that pervasive technology improves health is seen as one of the toughest challenges. Promising approaches are recently introduced, such as "clinical proof-of-concept" and balanced observational studies.
Conclusions: The paper concludes that pervasive healthcare will enable a paradigm shift from the established centralized healthcare model to a pervasive, user-centered and preventive overall lifestyle health management. In order to provide these new opportunities everywhere, anytime and to anyone, future research in the fields of pervasive sensing, pervasive prevention and evaluation of pervasive technology is inevitably needed.

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Methods Inf Med 2010; 49: 67–73
doi: 10.3414/ME09-02-0044
received: October 10, 2009
accepted: November 12, 2009
prepublished: December 8, 2009

1. Introduction

Before the 20th century, medical care was delivered at home, through visits from mobile family physicians who packed the necessary medical technology into a doctor's bag. In the 20th century rare and expensive resources, such as heavy technology and specialist providers, had to be centralized in hospitals to make their utilization effective [1]. Nowadays, the ageing of the population exerts pressure on the healthcare systems in various ways: increasing of chronic diseases and co-morbidity, problems of compliance to medication and lifestyle guidance among the elderly, and the need for long-term care and assistance of elderly people [2]. According to [3], a massive increase of chronic disease conditions and age-related illnesses are predicted as the dominant forces driving the future health care. Driven by quality and cost issues, the healthcare systems have to change radically in the near future from current healthcare professional-centric systems to distributed networked healthcare systems in which the individual becomes an active partner in the care process [4]. According to [5], there is the need to move from managing illness to maintaining wellness. In this transformation, pervasive technologies will play a major role [6]. Research on pervasive computing technologies for healthcare does not aim to replace traditional healthcare but is rather directed towards paving the way for a pervasive, user-centered and preventive healthcare model.

1.1 Pervasive Healthcare Definition

Pervasive healthcare may be defined from two perspectives: i) as the application of

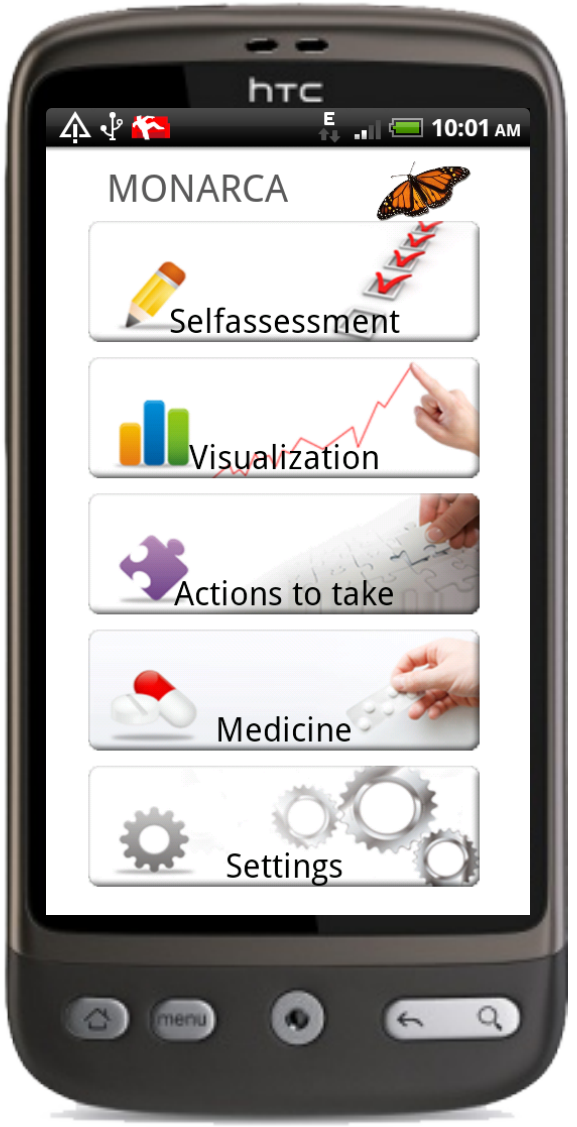
Methods Inf Med 1/2010

B Arnrich, O Mayora, JE Bardram, G Tröster. Pervasive healthcare: paving the way for a pervasive, user-centered and preventive healthcare model. *Methods Inf Med.* 2010;49(1):67-73.

MONARCA Project

- **Bipolar disorder** (manio-depressive)
- EU STREP project | **2010**-2014 | 13 partners
- **Copenhagen** team
  - Psychiatric Center Copenhagen (RegionH)
  - IT University of Copenhagen

- **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



User-centered Design

G Marcu, JE Bardram, S Gabrielli. A Framework for Overcoming Challenges in Designing Persuasive Monitoring Systems for Mental Illness. In *Proceedings of Pervasive Health* 2011, p.1-10, 2011

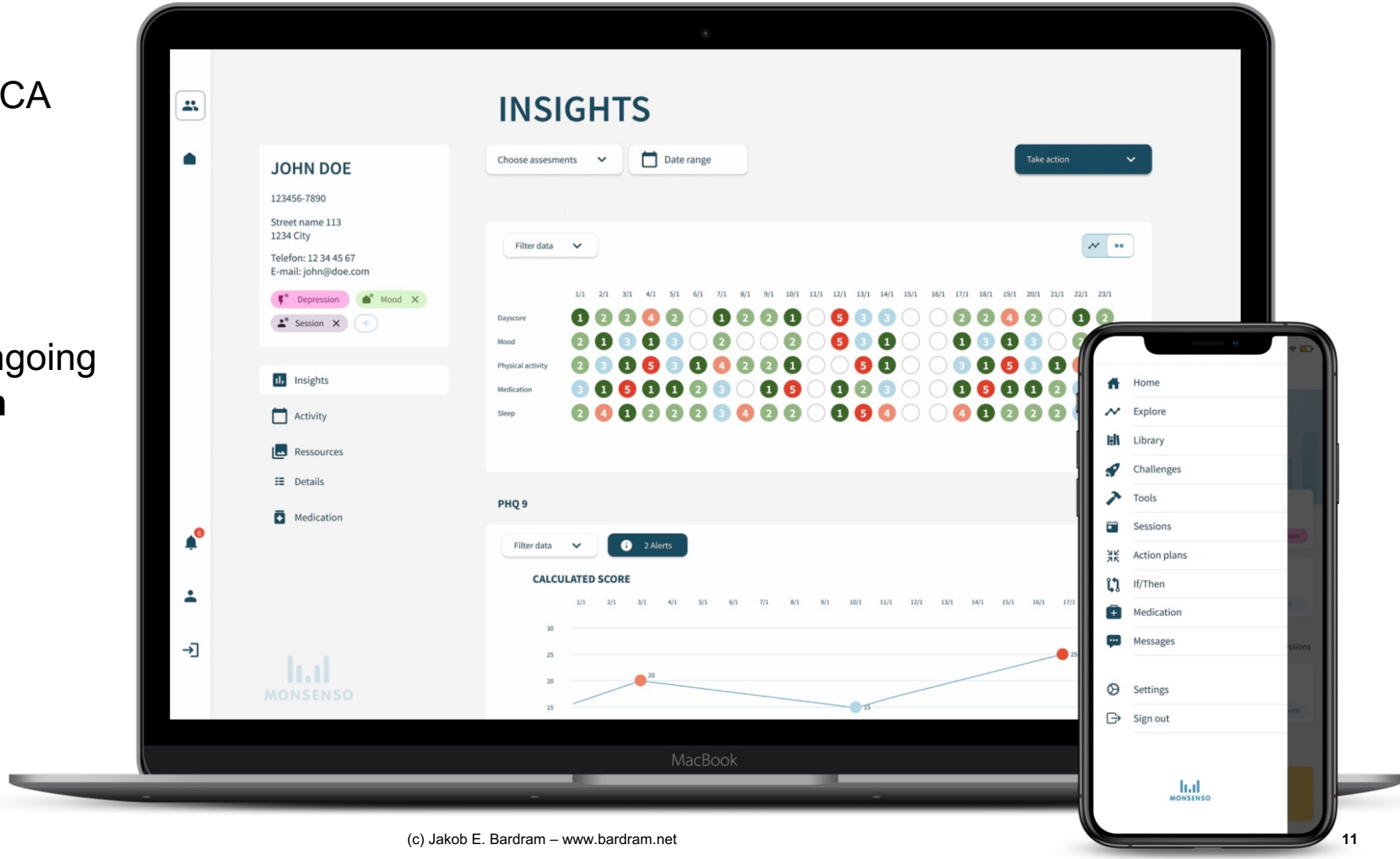
Double Loop

JE Bardram, MM Frost (2018). Double-loop health technology: enabling socio-technical design of personal health technology in clinical practice. In *Designing Healthcare That Works* (pp. 167-186). Academic Press.

Monsenso A/S

- **Founded 2015** based on the research done in the MONARCA project
- CE marked medical device
- Customers in 5+ countries

- The technological basis for ongoing **AI research in mental health**



AI IN MENTAL HEALTH

EXAMPLES

“AI” in Mental Health

Correlation

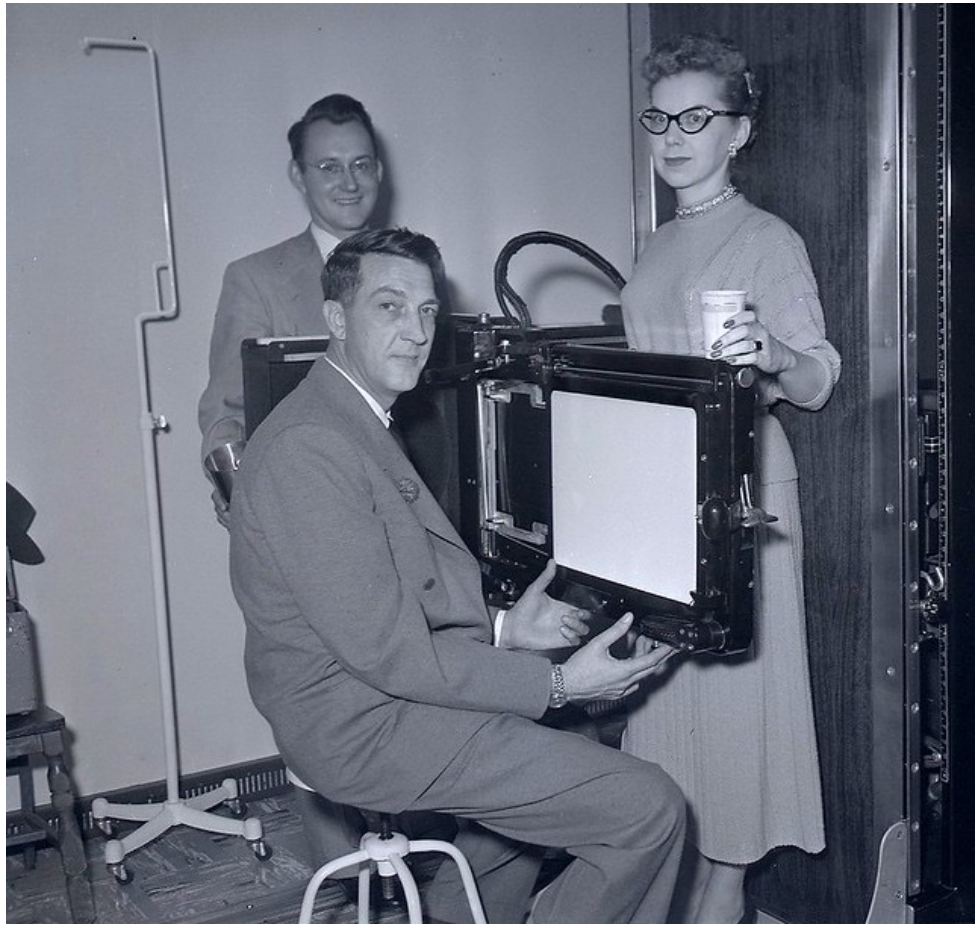
– self-reported mood
– mobility
– social activity
– physical activity
– voice

Classification

– disease classification
– state (e.g., manic/depressive episodes)

Prediction

– mood forecasting (1-5 days)
– relapse / remission
– readmission



X-Ray machine ca. 1950 [Wikipedia]

Correlations – Clinical

- Clinical Study
  - N=61 | 6 m | 19 m
  - HDRS-17 (depression) and YMRS (manic)
  - 400+ clinical ratings (monthly)
- Results
  - significant correlations between **self-rate** YMRS
  - significant correlations be ratings on both HDR
    - especially when gr tates' (3 states)

"Smartphones provide an **easy** and **objective** way to monitor illness activity and could serve as an **electronic biomarker** for depressive and manic symptoms in patients with bipolar disorder."

Table 2. Correlations between self-monitored data[a] collected using smartphones and depressive and manic symptoms measured using the HDRS-17 and YMRS, respectively[b]

	Unadjusted			Adjusted[c]		
	Coefficient	95% CI	p-value	Coefficient	95% CI	p-value
Mood (scale: −3 to +3)						
HDRS-17	−0.055	−0.067 to −0.042	<0.001	−0.058	−0.071 to −0.045	<0.001
HDRS-17 sub-item 1 (mood)	−0.38	−0.45 to −0.30	<0.001	−0.38	−0.46 to −0.31	<0.001
YMRS	0.39	0.016–0.062	<0.001	0.039	0.017–0.062	<0.001
YMRS sub-item 1 (mood)	0.38	0.24–0.53	<0.001	0.38	0.24–0.53	<0.001
Sleep (hours/night)						
HDRS-17	−0.017	−0.048 to 0.014	0.28	−0.02	−0.052 to 0.011	0.21
YMRS	−0.047	−0.088 to −0.005	0.027	−0.047	−0.088 to −0.006	0.026
Acti						
	−0.037	−0.053 to −0.020	<0.001	−0.042	−0.059 to −0.025	<0.001
	0.047	0.022–0.072	<0.001	0.048	0.023–0.072	<0.001
	047	0.029–0.065	<0.001	0.046	0.027–0.064	<0.001
	012	−0.013 to 0.033	0.34	0.012	−0.013 to 0.037	0.35

milton Depression Rating Scale–17 item; YMRS = Young Mania Rating Scale.
ere analyzed for the current day and three days before ratings with the HDRS-17 and YMRS, as symptoms over the last four days.
ge and sex.

Table 5. Correlations between automatically generated objective data [a] collected using smartphones and *affective states* according to the HDRS-17 and YMRS presented as categorical data [b], respectively[c]

	Unadjusted			Adjusted[d]		
	Coefficient	95% CI	p-value	Coefficient	95% CI	p-value
Incoming calls (no./day)						
Asymptomatic versus mania	0.95	0.076–1.82	0.033	0.97	0.10–1.84	0.029
Duration incoming calls (sec/day)						
Asymptomatic versus hypomania	729.51	334.87–1124.13	<0.001	768.10	374.34–1161.86	<0.001
Outgoing calls (no./day)						
Asymptomatic versus hypomania	2.09	0.38–3.80	0.016	2.08	0.37–3.80	0.017
Duration outgoing calls (sec/day)						
Asymptomatic versus moderate to severe depression	452.17	149.56–754.78	0.003	421.57	111.55–731.60	0.008
Asymptomatic versus hypomania	623.15	173.63–1072.67	0.007	641.53	190.41–1092.65	0.005
Outgoing text messages (no./day)						
Asymptomatic versus mania	4.14	−0.38 to 8.67	0.073	4.42	−0.10 to 8.95	0.055

CI = confidence interval; HDRS-17 = Hamilton Depression Rating Scale–17 item; YMRS = Young Mania Rating Scale.
[a]Averages of the smartphone data were analyzed for the current day and three days before ratings with the HDRS-17 and YMRS, as these rating scales address symptoms over the last four days.
[b]Scores on the HDRS-17 or YMRS ≤ 7 were defined as asymptomatic. Scores on the HDRS-17 or YMRS from 7 to 14 were defined as mild depression or hypomania. Scores on the HDRS-17 or YMRS ≥ 14 were defined as moderate to severe depression or mania.
[c]Analyses including all study participants; total N = 61.
[d]Adjusted for age and sex.

M Faurholt-Jepsen, M Vinberg, M Frost, EM Christensen, JE Bardram, LV Kessing. Smartphone data as an electronic biomarker of illness activity in bipolar disorder. *Bipolar Disorders*. 17(1): 2015

Correlations – Mobility & Depression

Study

- N = 28 | healthy / non-diagnosed subjects
- PHQ-8 self-rated depression score

Mobility Metrics

- The total distance covered ***D_T***
- The maximum distance between two l
- The radius of gyration ***G***
- The standard deviati ents
- The maximum distan me ***D_H***
- The number of differ t places visited ***N_{dif}***
- The number of different significant places vi
- The routine index ***R***

"significant correlation between **mobility trace** characteristics and depressive moods."

Mobility	Correlation		Average p-value	
	$T_{HIST} = 1$	$T_{HIST} = 14$	$T_{HIST} = 1$	$T_{HIST} = 14$
	[illegible]	0.402	0.401	0.095
	0.152	**0.432**	0.425	**0.069**
	0.160	0.343	0.422	0.197
σ_{dis}	0.147	0.417	0.431	0.088
D_H	0.199	0.358	0.297	0.168
N_{dif}	0.191	0.360	0.335	0.157
N_{sig}	0.201	0.336	0.385	0.181
R	**0.227**	0.368	**0.262**	0.138

Table 1: The averages of the absolute values of the correlations and of the p-values for different mobility metrics, for $T_{HIST} = 1$ day and $T_{HIST} = 14$ days.

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

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UbiComp '15, September 07-11, 2015, Osaka, Japan
© 2015 ACM. ISBN 978-1-4503-3574-4/15/09 $15.00
DOI: http://dx.doi.org/10.1145/2750858.2805845

L Canzian, M Musolesi. 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.

Correlations – Sensing & Mood

- Systematic review
  - behavioral features – mobile and wearable devices
  - depressive mood symptoms
  - patient w. affective disorders (unipolar & bipolar)

- 2,644 unique papers identified
  - 929 full papers screened
  - 46 papers included

- Studies divided into
  - clinical (i.e. , diagnosed) **N = 20**
  - non-clinical (”healthy individuals”) **N = 26**

JMIR MHEALTH AND UHEALTH Rohani et al

Review

Correlations Between Objective Behavioral Features Collected From Mobile and Wearable Devices and Depressive Mood Symptoms in Patients With Affective Disorders: Systematic Review

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Abstract

Background: Several studies have recently reported on the correlation between objective behavioral features collected via mobile and wearable devices and depressive mood symptoms in patients with affective disorders (unipolar and bipolar disorders). However, individual studies have reported on different and sometimes contradicting results, and no quantitative systematic review of the correlation between objective behavioral features and depressive mood symptoms has been published.

Objective: The objectives of this systematic review were to (1) provide an overview of the correlations between objective behavioral features and depressive mood symptoms reported in the literature and (2) investigate the strength and statistical significance of these correlations across studies. The answers to these questions could potentially help identify which objective features have shown most promising results across studies.

Methods: We conducted a systematic review of the scientific literature, reported according to the preferred reporting items for systematic reviews and meta-analyses guidelines. IEEE Xplore, ACM Digital Library, Web of Sciences, PsychINFO, PubMed, DBLP computer science bibliography, HTA, DARE, Scopus, and Science Direct were searched and supplemented by hand examination of reference lists. The search ended on April 27, 2017, and was limited to studies published between 2007 and 2017.

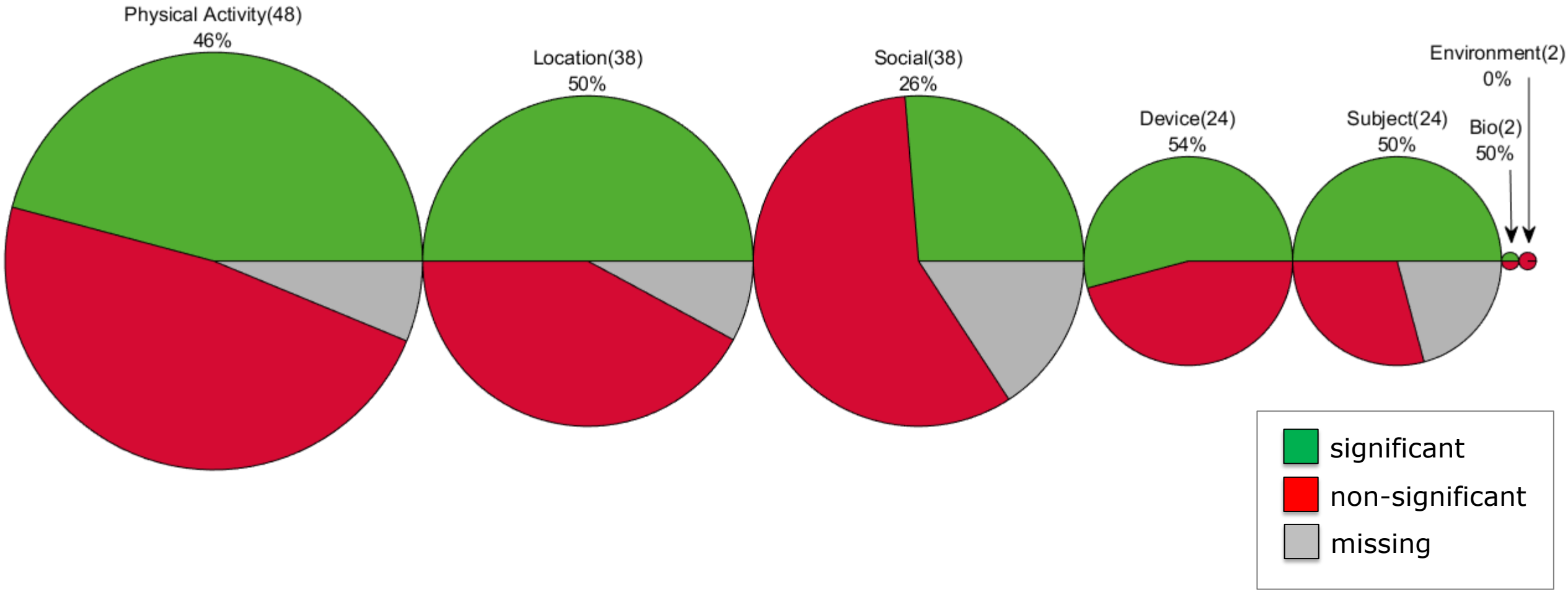
Results: A total of 46 studies were eligible for the review. These studies identified and investigated 85 unique objective behavioral features, covering 17 various sensor data inputs. These features were divided into 7 categories. Several features were found to have statistically significant and consistent correlation directionality with mood assessment (eg, the amount of home stay, sleep duration, and vigorous activity), while others showed directionality discrepancies across the studies (eg, amount of text messages [short message service] sent, time spent between locations, and frequency of mobile phone screen activity).

Conclusions: Several studies showed consistent and statistically significant correlations between objective behavioral features collected via mobile and wearable devices and depressive mood symptoms. Hence, continuous and everyday monitoring of behavioral aspects in affective disorders could be a promising supplementary objective measure for estimating depressive mood symptoms. However, the evidence is limited by methodological issues in individual studies and by a lack of standardization of (1) the collected objective features, (2) the mood assessment methodology, and (3) the statistical methods applied. Therefore, consistency in data collection and analysis in future studies is needed, making replication studies as well as meta-analyses possible.

(JMIR Mhealth Uhealth 2018;6(8):e165) doi:10.2196/mhealth.9691

AD Rohani, M Faurholt-Jepsen, LV Kessing, JE Bardram. Correlations Between Objective Behavioral Features Collected From Mobile and Wearable Devices and Depressive Mood Symptoms in Patients With Affective Disorders: Systematic Review. *JMIR Mhealth Uhealth*. 2018;6(8):e165.

Feature Categories



Classification – Bipolar vs. Healthy

- Bipolar Disorder (BD) vs. Healthy Controls (HC)
- N = 29 (BD) | 3
- Sensitivity
  - BD vs. HC : (
  - euthic vs. HC

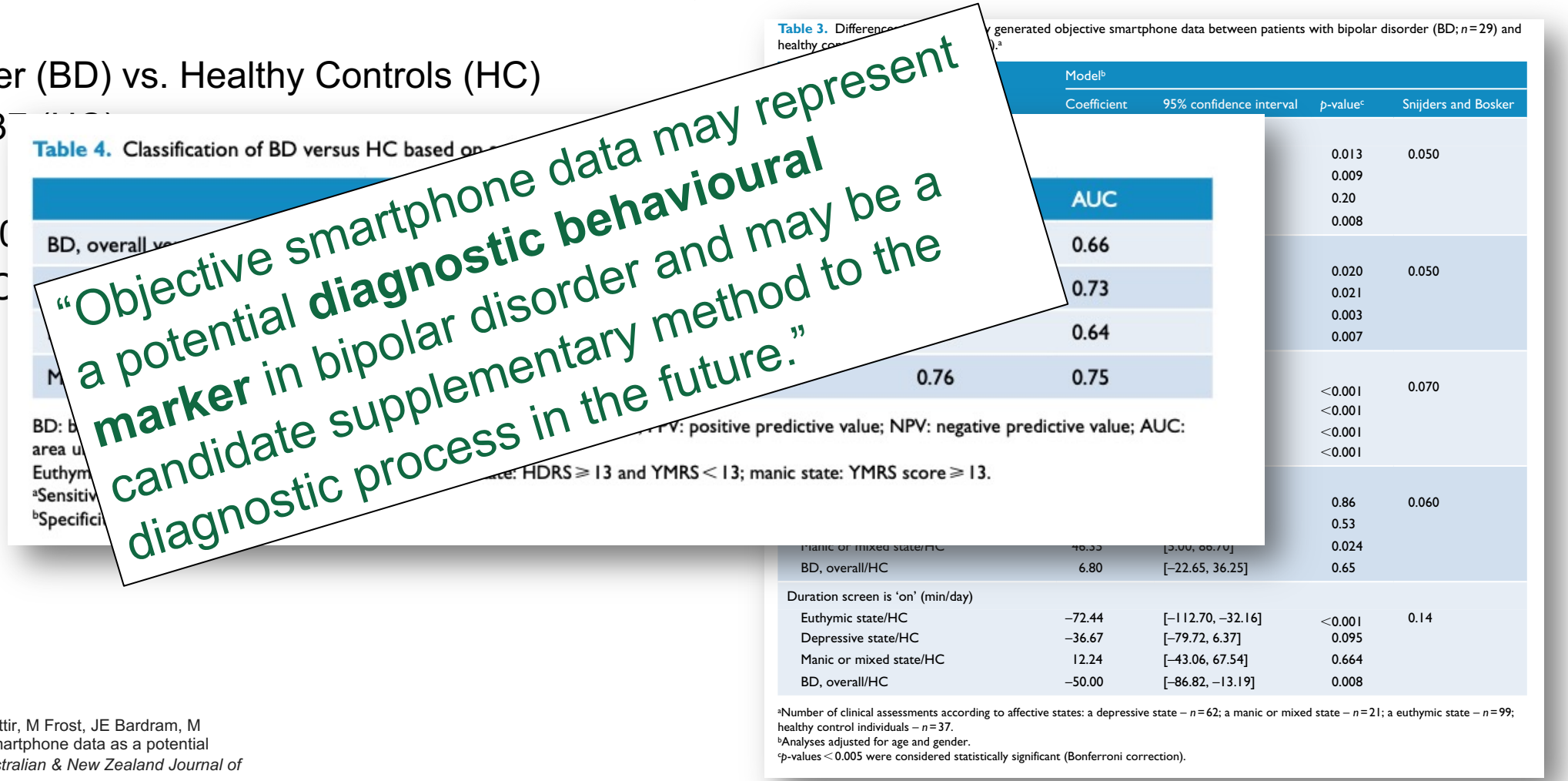


Table 3. Difference … generated objective smartphone data between patients with bipolar disorder (BD; *n* = 29) and healthy co…).[a]

	Model[b]			
	Coefficient	95% confidence interval	*p*-value[c]	Snijders and Bosker
			0.013	0.050
			0.009	
			0.20	
			0.008	
			0.020	0.050
			0.021	
			0.003	
			0.007	
			<0.001	0.070
			<0.001	
			<0.001	
			<0.001	
			0.86	0.060
			0.53	
			0.024	
BD, overall/HC	6.80	[–22.65, 36.25]	0.65	
Duration screen is 'on' (min/day)				
Euthymic state/HC	–72.44	[–112.70, –32.16]	<0.001	0.14
Depressive state/HC	–36.67	[–79.72, 6.37]	0.095	
Manic or mixed state/HC	12.24	[–43.06, 67.54]	0.664	
BD, overall/HC	–50.00	[–86.82, –13.19]	0.008	

[a]Number of clinical assessments according to affective states: a depressive state – *n* = 62; a manic or mixed state – *n* = 21; a euthymic state – *n* = 99; healthy control individuals – *n* = 37.
[b]Analyses adjusted for age and gender.
[c]*p*-values < 0.005 were considered statistically significant (Bonferroni correction).

Table 4. Classification of BD versus HC based on …

	AUC
BD, overall	0.66
	0.73
	0.64
M…	0.76 0.75

BD: b… area u… Euthym… [a]Sensitiv… [b]Specifici… …PV: positive predictive value; NPV: negative predictive value; AUC: …te: HDRS ≥ 13 and YMRS < 13; manic state: YMRS score ≥ 13.

"Objective smartphone data may represent a potential **diagnostic behavioural marker** in bipolar disorder and may be a candidate supplementary method to the diagnostic process in the future."

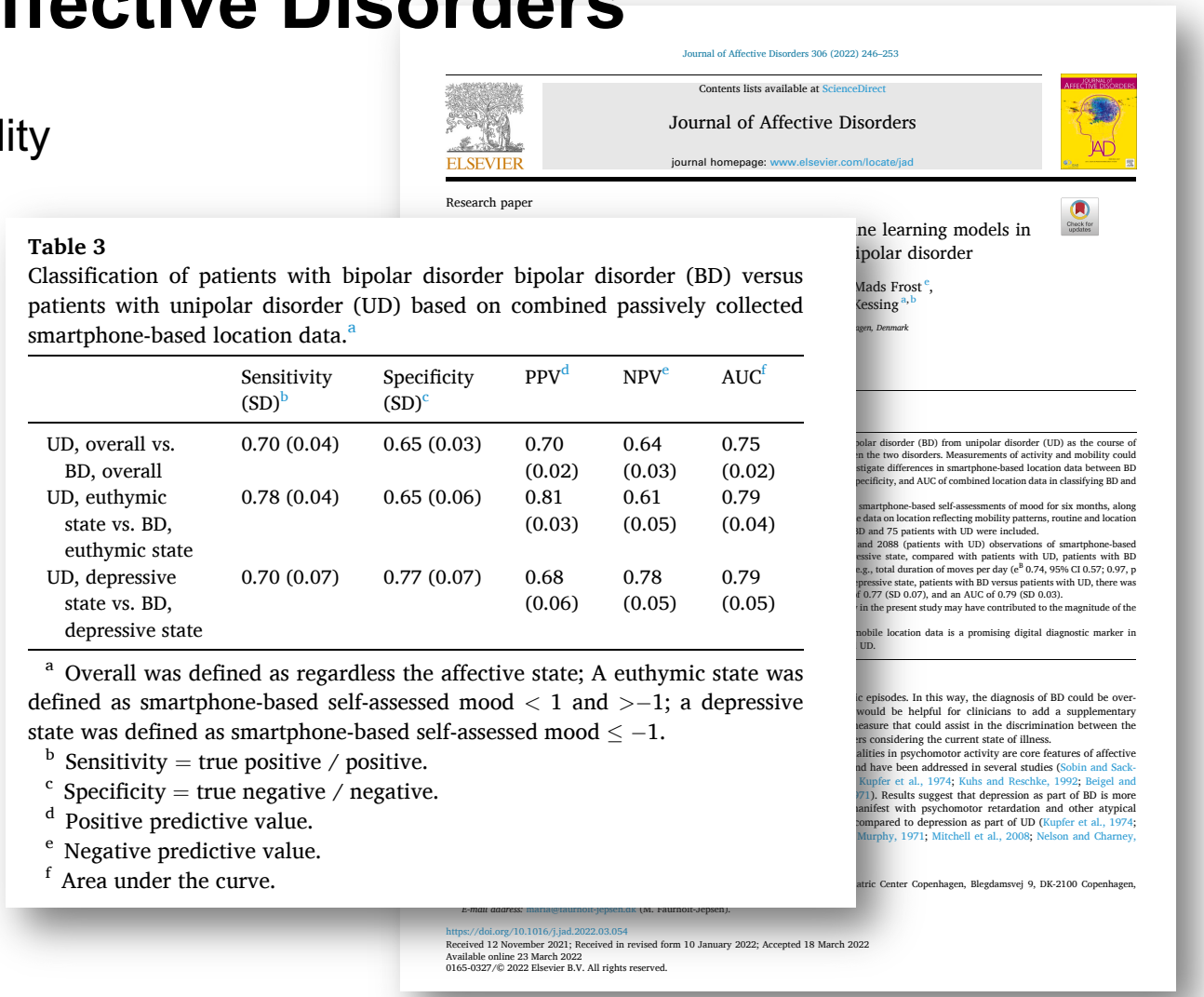
M Faurholt-Jepsen, J Busk, H Þórarinsdóttir, M Frost, JE Bardram, M Vinberg, LV Kessing (2019). Objective smartphone data as a potential diagnostic marker of bipolar disorder. *Australian & New Zealand Journal of Psychiatry*, *53*(2), 119-128.

Classification – Mobility & Affective Disorders

- Classification of affective disorders based on mobility patterns
  - bipolar disorder (mania-depression)
  - unipolar disorder (depression)

- T = 6 months
- N = 65 (BD) | N = 75 (UD)

- Mobility Features
  - no. stops
  - duration stops
  - ...
  - location entrophy



Journal of Affective Disorders 306 (2022) 246–253

Contents lists available at ScienceDirect

Journal of Affective Disorders

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Research paper

ne learning models in
ipolar disorder

Mads Frost [e],
Kessing [a,b]

agen, Denmark

Table 3
Classification of patients with bipolar disorder bipolar disorder (BD) versus patients with unipolar disorder (UD) based on combined passively collected smartphone-based location data.[a]

	Sensitivity (SD)[b]	Specificity (SD)[c]	PPV[d]	NPV[e]	AUC[f]
UD, overall vs. BD, overall	0.70 (0.04)	0.65 (0.03)	0.70 (0.02)	0.64 (0.03)	0.75 (0.02)
UD, euthymic state vs. BD, euthymic state	0.78 (0.04)	0.65 (0.06)	0.81 (0.03)	0.61 (0.05)	0.79 (0.04)
UD, depressive state vs. BD, depressive state	0.70 (0.07)	0.77 (0.07)	0.68 (0.06)	0.78 (0.05)	0.79 (0.05)

[a] Overall was defined as regardless the affective state; A euthymic state was defined as smartphone-based self-assessed mood < 1 and > -1; a depressive state was defined as smartphone-based self-assessed mood ≤ -1.
[b] Sensitivity = true positive / positive.
[c] Specificity = true negative / negative.
[d] Positive predictive value.
[e] Negative predictive value.
[f] Area under the curve.

olar disorder (BD) from unipolar disorder (UD) as the course of
n the two disorders. Measurements of activity and mobility could
stigate differences in smartphone-based location data between BD
pecificity, and AUC of combined location data in classifying BD and

smartphone-based self-assessments of mood for six months, along
e data on location reflecting mobility patterns, routine and location
D and 75 patients with UD were included.
and 2088 (patients with UD) observations of smartphone-based
essive state, compared with patients with UD, patients with BD
e.g., total duration of moves per day (e[β] 0.74, 95% CI 0.57; 0.97, p
pressive state, patients with BD versus patients with UD, there was
f 0.77 (SD 0.07), and an AUC of 0.79 (SD 0.03).
in the present study may have contributed to the magnitude of the

mobile location data is a promising digital diagnostic marker in
UD.

ic episodes. In this way, the diagnosis of BD could be over-
would be helpful for clinicians to add a supplementary
easure that could assist in the discrimination between the
rs considering the current state of illness.
alities in psychomotor activity are core features of affective
nd have been addressed in several studies (Sobin and Sack-
Kupfer et al., 1974; Kuhs and Reschke, 1992; Beigel and
71). Results suggest that depression as part of BD is more
anifest with psychomotor retardation and other atypical
compared to depression as part of UD (Kupfer et al., 1974;
Murphy, 1971; Mitchell et al., 2008; Nelson and Charney,

atric Center Copenhagen, Blegdamsvej 9, DK-2100 Copenhagen,

E-mail address: maria@faurholt-jepsen.dk (M. Faurholt-Jepsen).

https://doi.org/10.1016/j.jad.2022.03.054
Received 12 November 2021; Received in revised form 10 January 2022; Accepted 18 March 2022
Available online 23 March 2022
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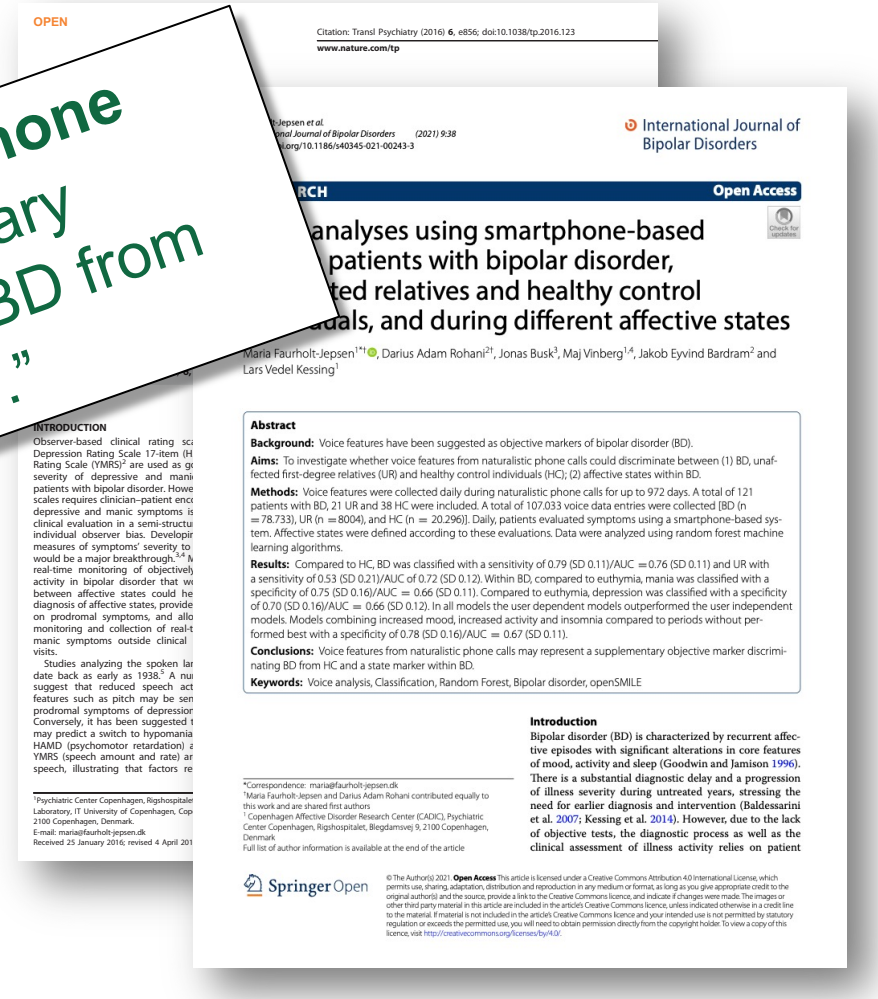
M Faurholt-Jepsen, J Busk, DA Rohani, M Frost, M Tønning, JE Bardram, LV Kessing (2022). Differences in mobility patterns according to machine learning models in patients with bipolar disorder and patients with unipolar disorder. *Journal of Affective Disorders*, *306*, 246-253.

Classification – Voice & Mood (2016 & 2021)

Collection of voice features in naturalistic setting
- N=180 | 972 days
- clinical rating :: HDRS-17 (depression) an
- openSMILE (emolarge)

Classification results (use
- depressive state :
- manic state : 75% (
- bipolar state : 79% (

"Voice features from **naturalistic phone calls** may represent a supplementary **objective marker** discriminating BD from HC and a state marker within BD."


OPEN

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

International Journal of Bipolar Disorders

Open Access

analyses using smartphone-based
patients with bipolar disorder,
ted relatives and healthy control
duals, and during different affective states

Maria Faurholt-Jepsen[1*†], Darius Adam Rohani[2†], Jonas Busk[3], Maj Vinberg[1,4], Jakob Eyvind Bardram[2] and Lars Vedel Kessing[1]

Abstract

Background: Voice features have been suggested as objective markers of bipolar disorder (BD).

Aims: To investigate whether voice features from naturalistic phone calls could discriminate between (1) BD, unaffected first-degree relatives (UR) and healthy control individuals (HC); (2) affective states within BD.

Methods: Voice features were collected daily during naturalistic phone calls for up to 972 days. A total of 121 patients with BD, 21 UR and 38 HC were included. A total of 107.033 voice data entries were collected [BD (n = 78.733), UR (n = 8004), and HC (n = 20.296)]. Daily, patients evaluated symptoms using a smartphone-based system. Affective states were defined according to these evaluations. Data were analyzed using random forest machine learning algorithms.

Results: Compared to HC, BD was classified with a sensitivity of 0.79 (SD 0.11)/AUC = 0.76 (SD 0.11) and UR with a sensitivity of 0.53 (SD 0.21)/AUC of 0.72 (SD 0.12). Within BD, compared to euthymia, mania was classified with a specificity of 0.75 (SD 0.16)/AUC = 0.66 (SD 0.11). Compared to euthymia, depression was classified with a specificity of 0.70 (SD 0.16)/AUC = 0.66 (SD 0.12). In all models the user dependent models outperformed the user independent models. Models combining increased mood, increased activity and insomnia compared to periods without performed best with a specificity of 0.78 (SD 0.16)/AUC = 0.67 (SD 0.11).

Conclusions: Voice features from naturalistic phone calls may represent a supplementary objective marker discriminating BD from HC and a state marker within BD.

Keywords: Voice analysis, Classification, Random Forest, Bipolar disorder, openSMILE

Introduction

Bipolar disorder (BD) is characterized by recurrent affective episodes with significant alterations in core features of mood, activity and sleep (Goodwin and Jamison 1996). There is a substantial diagnostic delay and a progression of illness severity during untreated years, stressing the need for earlier diagnosis and intervention (Baldessarini et al. 2007; Kessing et al. 2014). However, due to the lack of objective tests, the diagnostic process as well as the clinical assessment of illness activity relies on patient

M Faurholt-Jepsen, J Busk, M Frost, M Vinberg, EM Christensen, O Winther, JE Bardram, LV Kessing (2016,). Voice analysis as an objective state marker in bipolar disorder. *Transl Psychiatry*. Macmillan Publishers Limited.

M Faurholt-Jepsen, DA Rohani, J Busk, M Vinberg, JE Bardram, LV Kessing (2021). Voice analyses using smartphone-based data in patients with bipolar disorder, unaffected relatives and healthy control individuals, and during different affective states. International Journal of Bipolar Disorders, 9, 1-13.

Prediction – Mood & Clinical Rating

- N=84 bipolar patients
- Self-reported data
  – activity | alcohol | mood | cognition |
- Prediction of **mood** up to 7 days
- Prediction of **clinical ratings**

JMIR MHEALTH AND UHEALTH Busk et al

Original Paper

Forecasting Mood in Bipolar Disorder From Smartphone Self-assessments: Hierarchical Bayesian Approach

Figure 6. Results of forecasting mood for up to seven days. The root mean squared error (RMSE) was evaluated in time-series cross-validation experiments for w=4 and h=1 through 7. As expected, the RMSE increases when forecasting further ahead. The proposed hierarchical models achieved consistently lower RMSEs than the baseline models.

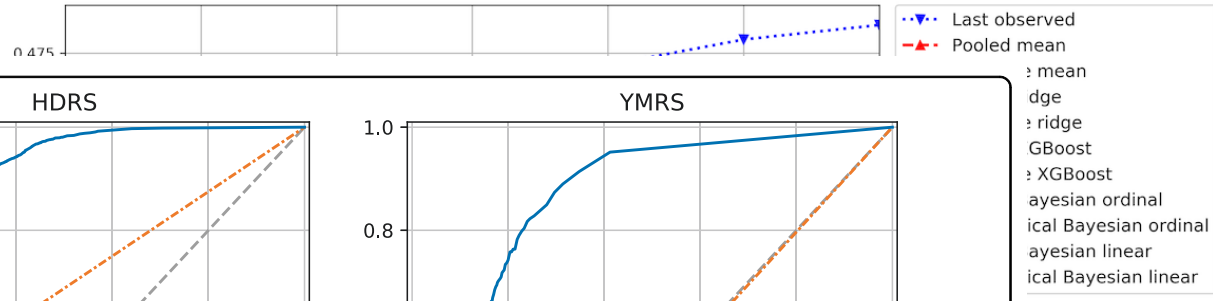


Fig. 2 Results of predicting relapse risk scores evaluated as a binary classification problem and presented in receiver operating characteristic (ROC) curves. In both the HDRS case (left) and the YMRS case (right), the hierarchical Bayesian regression model outperforms naïve pooled and separate mean models.

J Busk, M Faurholt-Jepsen, M Frost, JE Bardram, LV Kessing, O Winther (2020). Forecasting mood in bipolar disorder from smartphone self-assessments: hierarchical bayesian approach. *JMIR mHealth and uHealth*, *8*(4), e15028.

Prediction – Mobility & Depression

"Is it possible to monitor and diagnose a depressed mood by looking at the mobility trace collected from a smartphone of an individual?"

Study

- N = 28 | healthy / non-diagnosed sub
- Predict the situation in which the use
  significantly larger than its usual valu

"It is possible to develop **inference algorithms** for unobtrusive monitoring and **prediction** of depressive mood disorders."

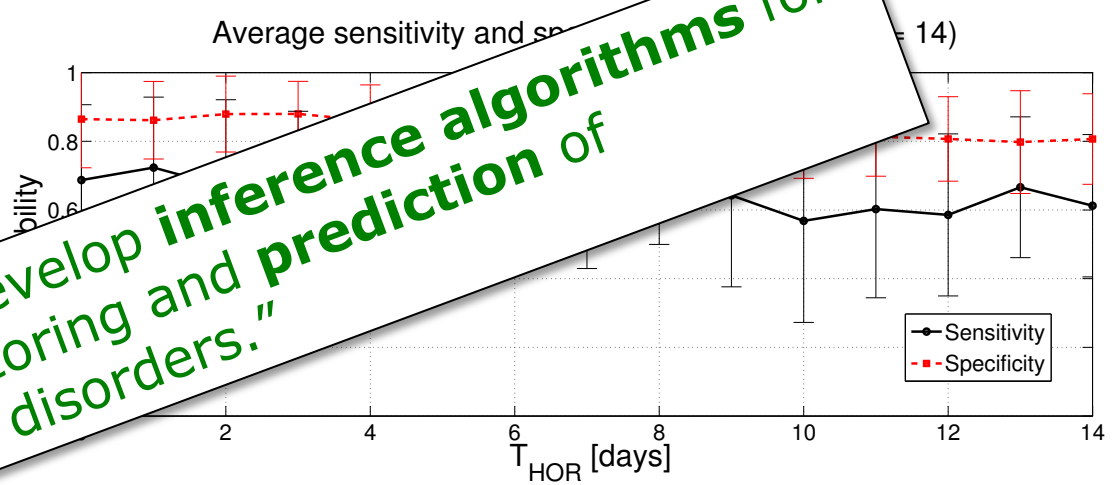
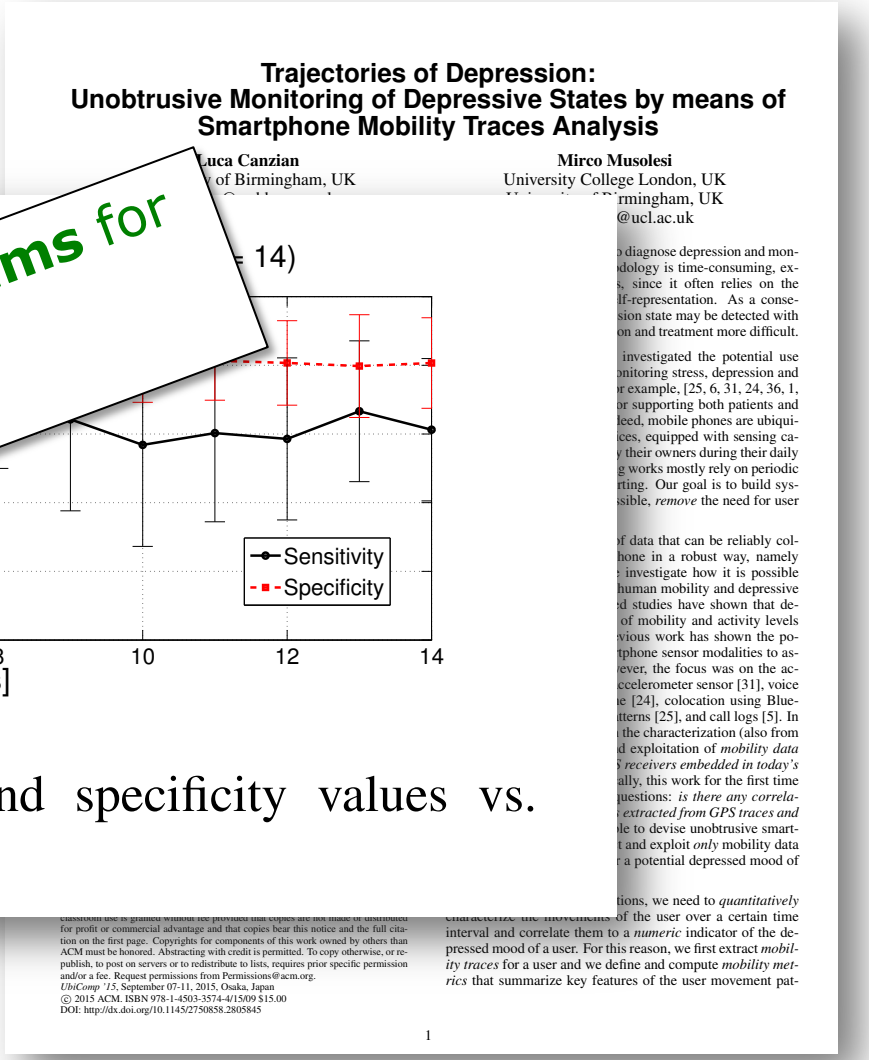


Figure 9: Average sensitivity and specificity values vs. T_{HOR}, for $T_{HIST} = 14$ days.


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

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L Canzian, M Musolesi. 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.

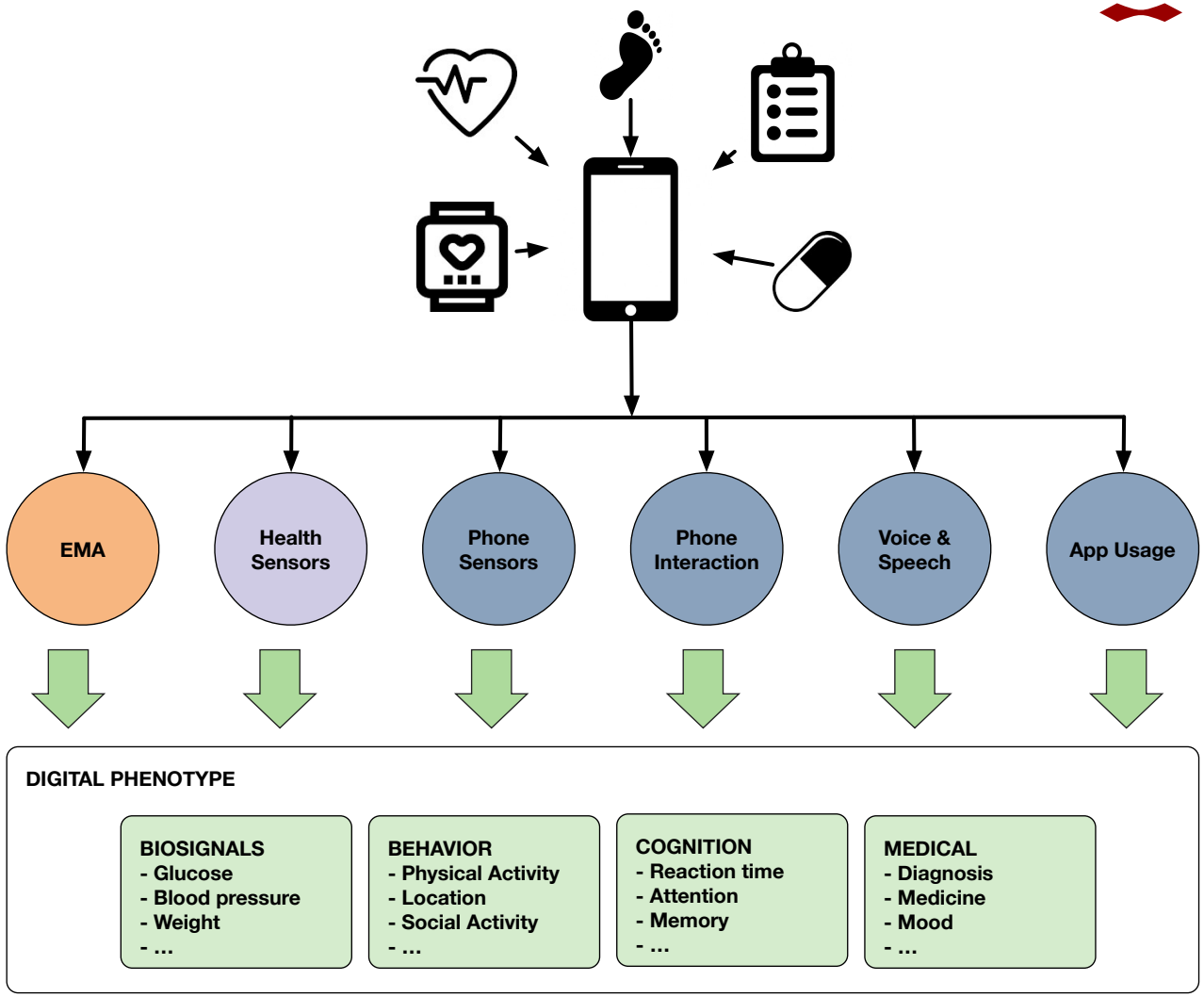
WHAT DOES ALL THIS MEAN?

Status 2024 (Affective Disorders)

- Can smartphone-based **self-assessment** of mood be used clinically?
- Is there a correlation between **automatically sensed behavioral** markers and mental health?
- Can we **classify persons with mental health problems** compared to healthy subjects?
- Can we **classify the state** of mental health problems?
- Can we **predict the mood of a patient** with mental health problems?

Digital Phenotyping

- **Continuous**
  - 24/7, longitudinal,
- **Ambulatory**
  - “in-the-wild”, at home, ...
- **Unobtrusive**
  - consumer / everyday technology
  - mobile / wearable sensing
- **Large N’s**
  - large-scale deployment
  - “cheap” technology
- **Inference**
  - of behavior, cognition, health
  - based on health data science (AI/ML)



SH Jain, BW Powers, JB Hawkins, JS Brownstein (2015). The digital phenotype. *Nat Biotech*, 33(5), 462–463.

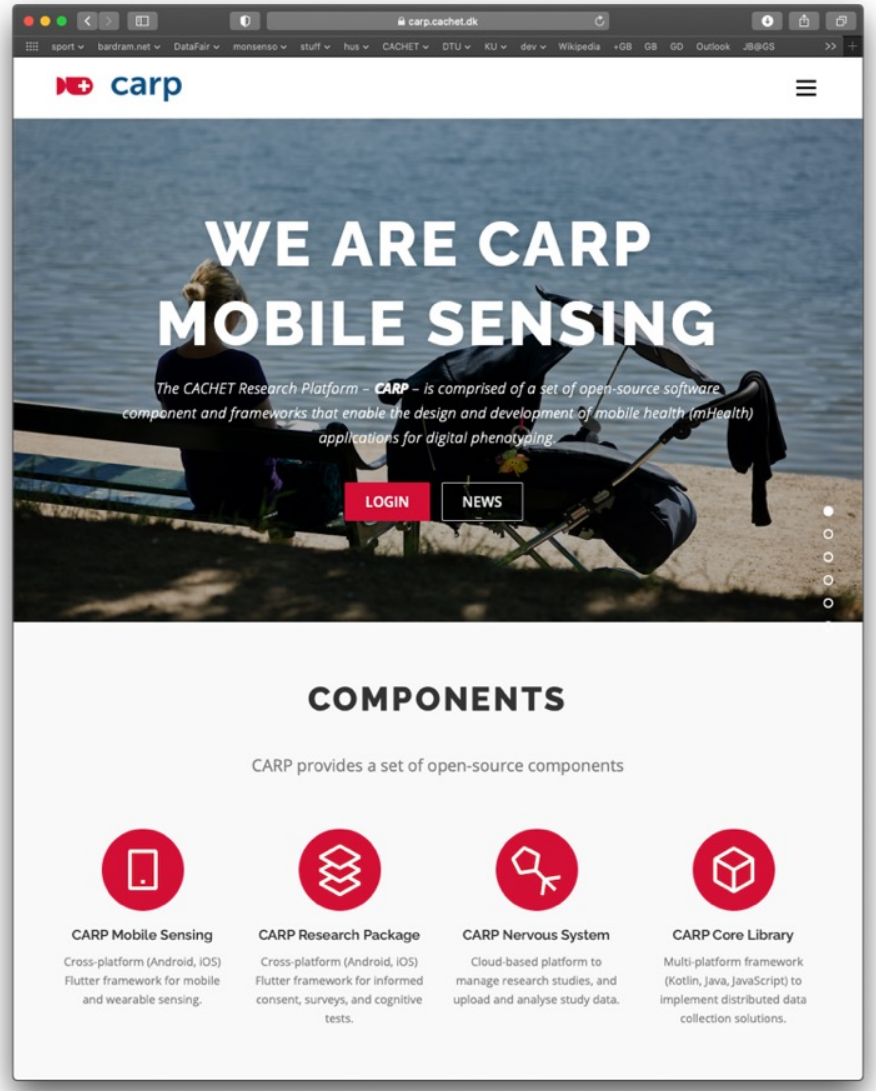
TR Insel (2017). Digital phenotyping: Technology for a new science of behavior. *JAMA*, *318*(13), 1215–1216.

Copenhagen Research Platform – CARP

carp.cachet.dk

Large-scale data science platform for digital phenotyping and personal health technology

- **Open source [programming] framework**
  - multi-project platform used in many mHealth applications
  - developed and shared w industry partners
- **Sharing**
  - multi-study platform
  - analysis of data across multiple studies
- **Privacy & Security**
  - enabling privacy & security as part of platform (GDPR)
  - secure local hosting @ DTU Computerome
- **Standardization**
  - part of open international standards
  - FHIR, IEEE 1752, ORK, ORS, ...



QUESTIONS?

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