

# DIGITAL PHENOTYPING

TECHNOLOGIES FOR COLLECTION AND IDENTIFICATION OF  
DIGITAL BIOMARKERS IN NEUROLOGY AND MENTAL HEALTH

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# About me

## Jakob E. Bardram

- Professor in **Digital Health** at **DTU Health Tech**
  - background in computer science, economics, and psychology
  - University of Aarhus (AU) & University of California at Irvine (UCI)
- Professor at AU and ITU before joining **DTU** in 2015
- Primary teaching & research areas
  - programming & **software** architecture (object-oriented)
  - **data** analysis (AI/ML)
  - **medical informatics** – electronic patient records, clinical logistics, standards
  - **mobile health** – psychiatry, neurology, diabetes, cardiology
- Entrepreneur
  - **co-founder** of 4 companies – e.g., Cetrea A/S and Monsenso A/S

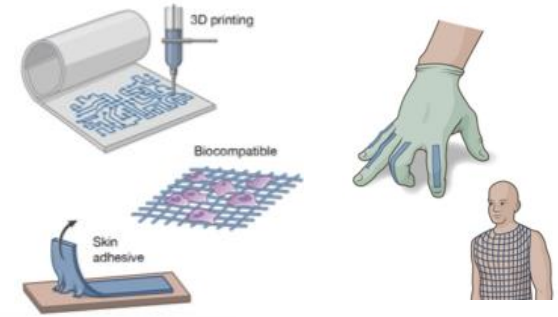


[www.bardram.net](http://www.bardram.net)

# Digital Health at DTU Health Tech

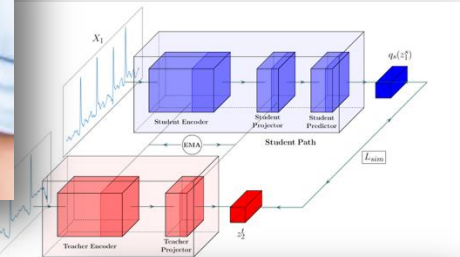
#1

Biocompatible and flexible electronics for wearable and implantable sensor technology



#2

Biomedical signal processing and health data science



#3

Personalized health technology and digital phenotyping



# Outline

## DIGITAL PHENOTYPING

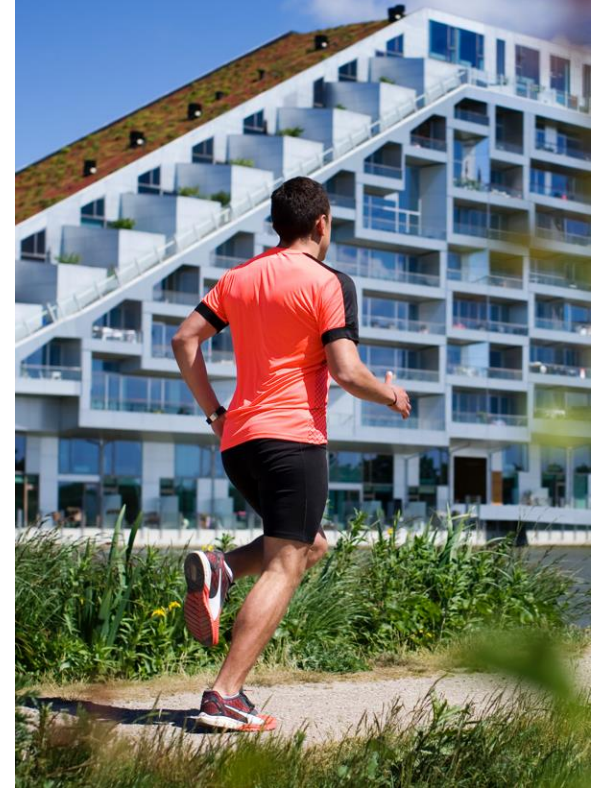
- Digital Phenotyping
- Digital Biomarkers

## COPENHAGEN RESEARCH PLATFORM (CARP)

- Components
- Data collection | Devices | PRO | Cognition

## CASES

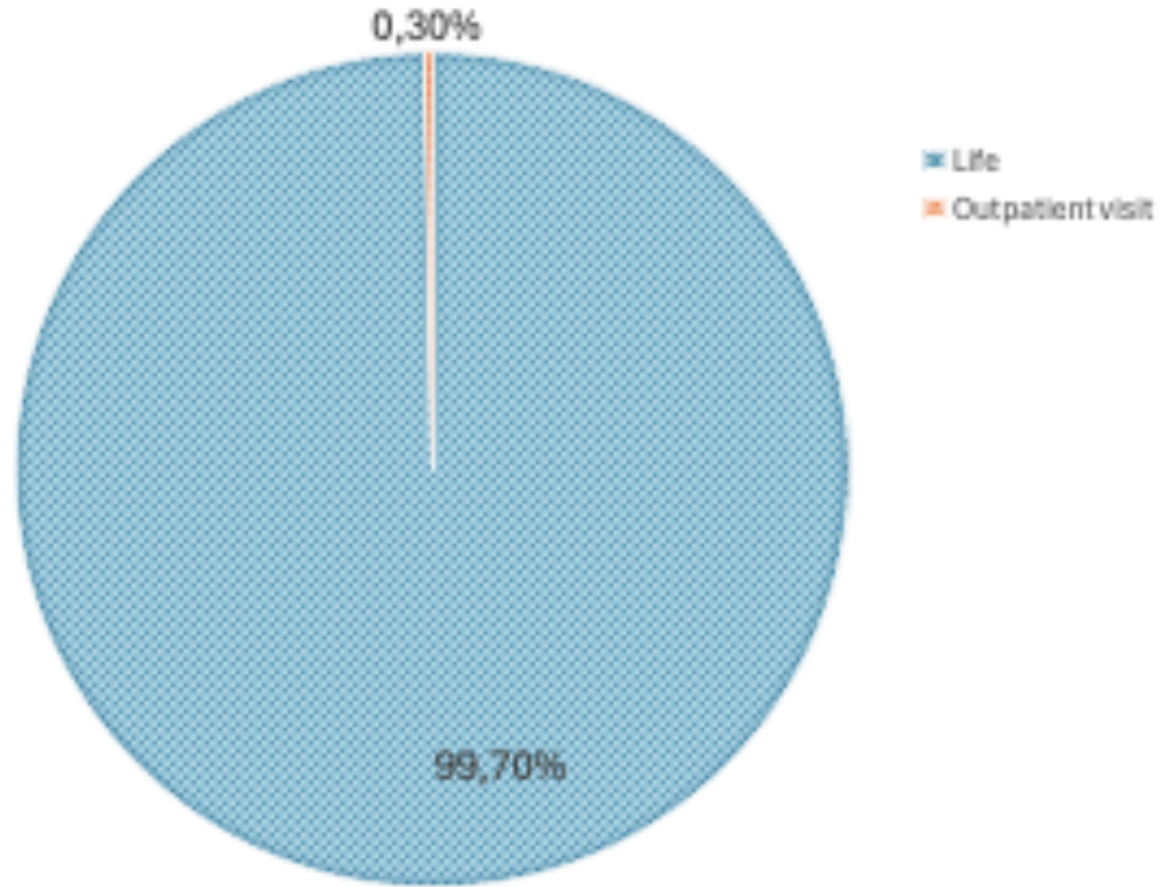
- Psychology
- Psychiatry
- Neurology





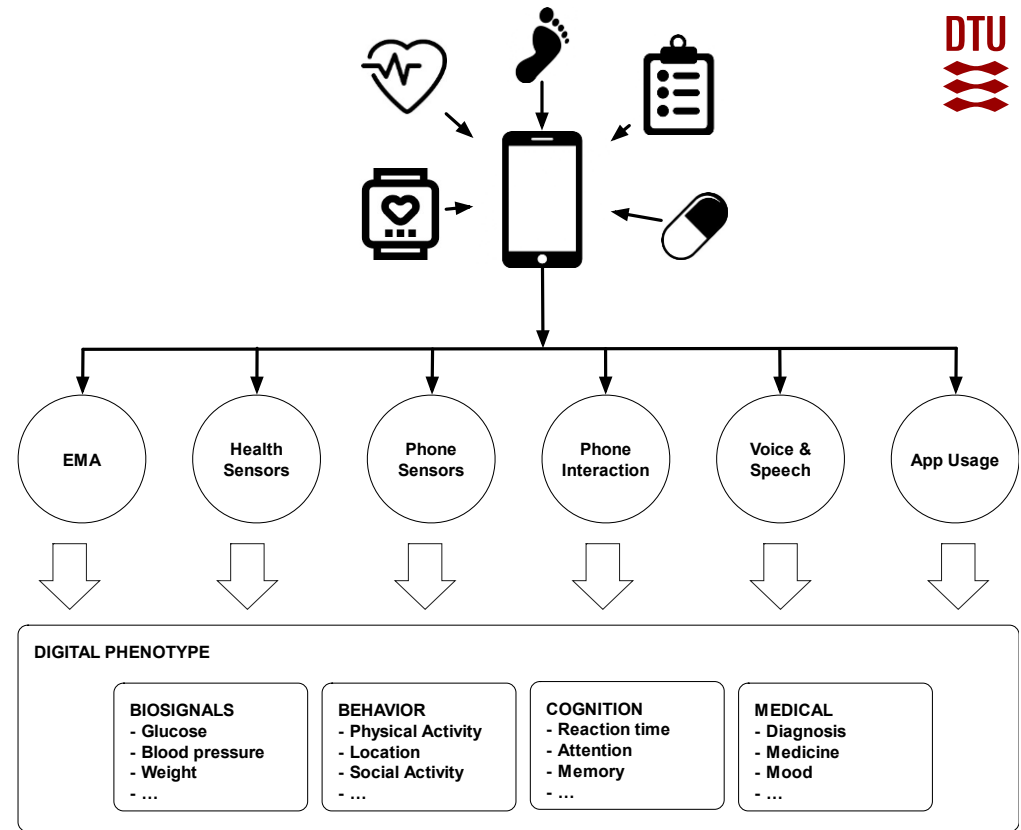
# Digital Phenotyping





















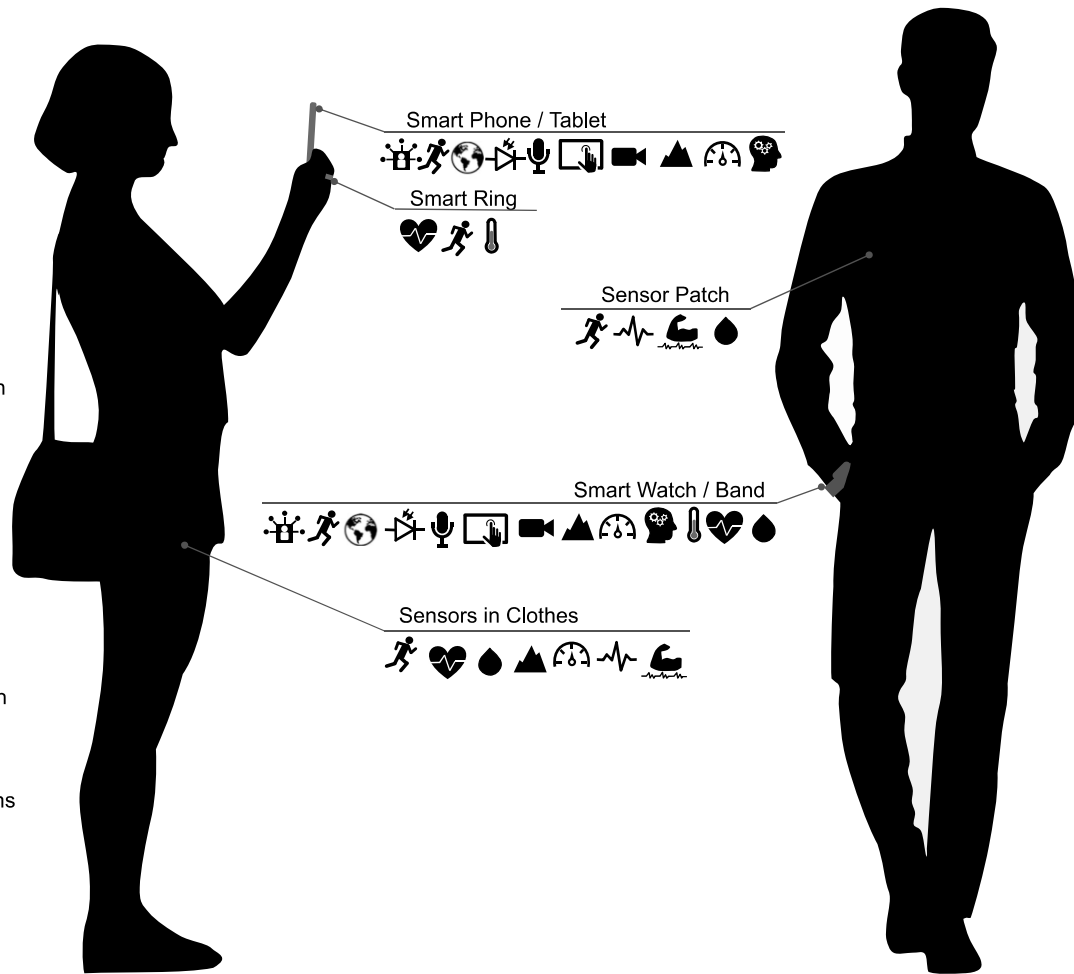
# Digital Phenotyping

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



- JP Onnela & SL Rauch (2016). Harnessing Smartphone-Based Digital Phenotyping to Enhance Behavioral and Mental Health. *Neuropsychopharmacology*. 41(7): 1691–1696.
- 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.

-  Microphone
-  Touch Screen
-  Camera
-  Altimeter
-  Barometer
-  PPG
-  ElectroCardioGraph
-  IMU
-  Geo-Positioning
-  Light Sensor
-  Thermometer
-  ElectroMyoGraph
-  ElectroDermoGraph
-  Logic
-  Wireless Interactions
-  Social Network



Kourtis, L. C., Regele, O. B., Wright, J. M., & Jones, G. B. (2019). Digital biomarkers for Alzheimer's disease: the mobile/wearable devices opportunity. *NPJ digital medicine*, 2(1), 9.



# Biomarkers & Digital Biomarkers

- **Biomarker** [1]

- a defined characteristic
- that is measured as an **indicator** of normal biological processes, pathogenic processes, or biological responses to an exposure or intervention, including therapeutic interventions
- e.g., **blood pressure**

- **Digital biomarker** [2]

- a characteristic or set of characteristics
- collected from **digital health technologies**,
- that is measured as an **indicator** of normal biological processes, pathogenic processes, or responses to an exposure or intervention, including therapeutic interventions.
- e.g., **location entropy** extracted from the phone's GPS as an early indicator of depression
- e.g., **cardiovascular features** extracted from wearable devices to identify atrial fibrillation

1. U.S. Food and Drug Administration. Patient-Focused Drug Development: Collecting Comprehensive and Representative Input. Final guidance document.

2. Vasudevan, S., Saha, A., Tarver, M.E. *et al.* Digital biomarkers: Convergence of digital health technologies and biomarkers. *npj Digit. Med.* 5, 36 (2022).

# The Copenhagen Research Platform (CARP)

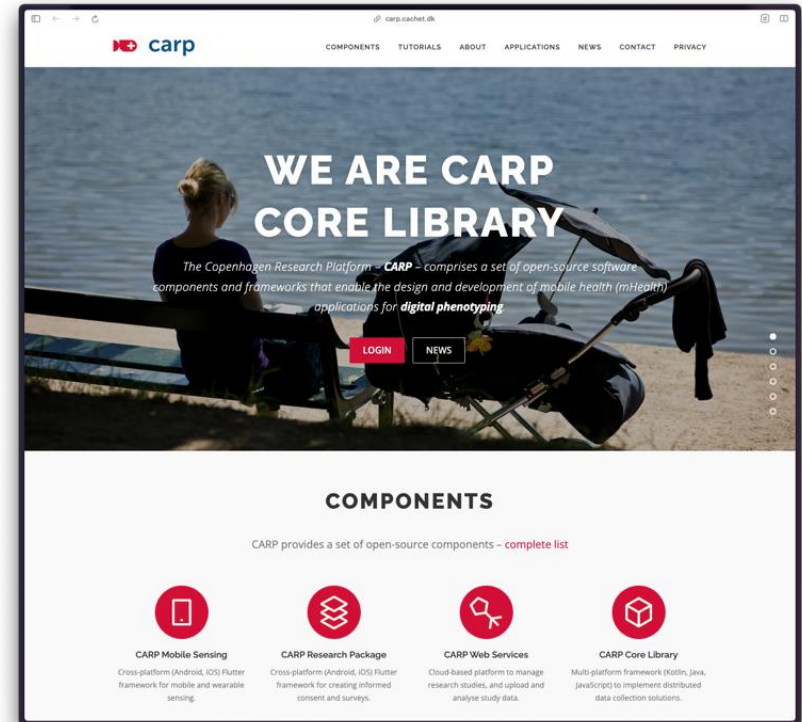


I klinikken

# Copenhagen Research Platform – CARP

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

- **Open-source programming framework**
  - components & frameworks for the design of mHealth applications
  - used to create disease-specific solutions
  - developed and shared with research & industry partners (open source)
- **“Out-of-the-Box” Study Hosting**
  - CARP instance hosted @DTU Computerome (HPC)
  - GDPR compliant for Danish researchers
  - configurable study setup
  - standard participant phone app
  - large-scale analysis of data



[carp.dk](http://carp.dk)

# CARP Components



## CARP Core

- domain model and standards



## CARP Mobile Sensing (CAMS)

- mobile & wearable sensing framework



## CARP Research Package

- informed consent & survey framework



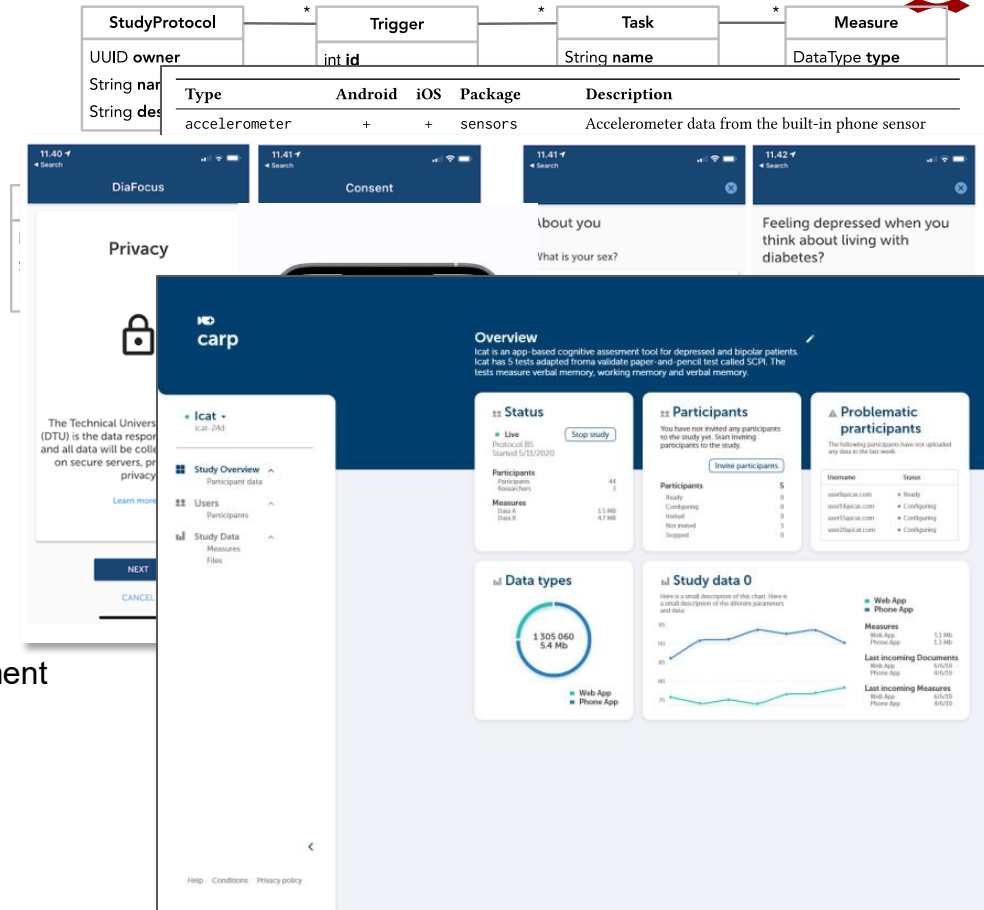
## CARP Cognition Package

- cognitive test framework incl. 14 pre-made tests



## CARP Web Services (CAWS)

- cloud-based infrastructure for data management





# Data Collection

## Physiological

- weight, height, ...
- ECG, HR, HRV, blood pressure...
- Blood glucose

## Behavioral

- physical activity (steps, movement, ...)
- social activity (communication, calendar, messaging, ...)
- phone usage (screen, connectivity, ...)

## Contextual

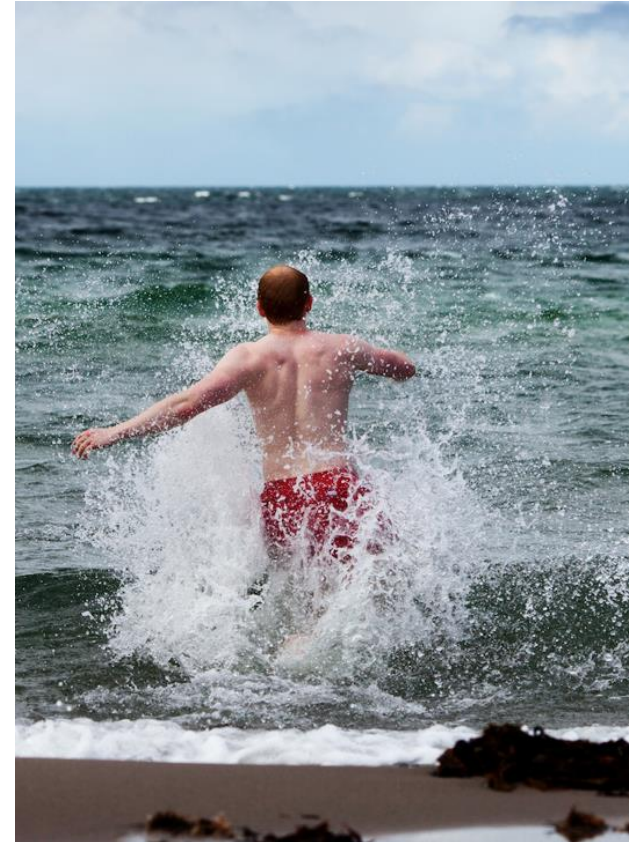
- location (geo-position, geofence, ...)
- weather, air quality

## Patient-Reported

- surveys
- ecological momentary assessments (EMA)
- audio & video

## Cognition

- 8 Neurocognitive domains
- 14 validated gold-standard cognitive tests



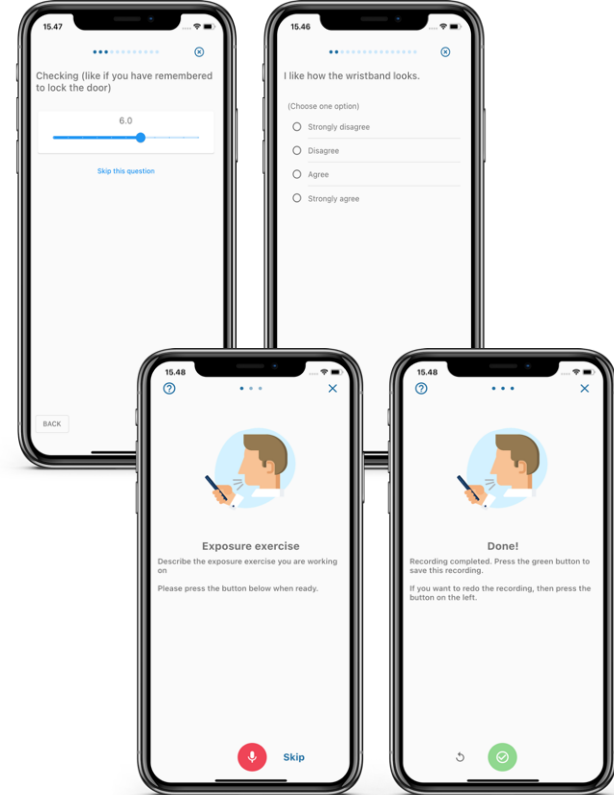
# Plug-in Model for Devices

- Movisens (activity, ECG, EDA)
  - Nokia Bell Labs eSense (noise, activity)
  - Polar Sense & H10 (HR/ECG)
  - Empatica E4 (HR, GSR, activity)
  - Dexcom (CGM)
- 
- Apple Health
  - Google Health Connect
- 
- Dexcom (CGM)
  - Garmin (activity, sleep, HR, ...)
  - Fitbit (activity, sleep, HR, BP, ECG, weight,
  - Withings (activity, sleep, HR, BP, ECG, weight, ...)



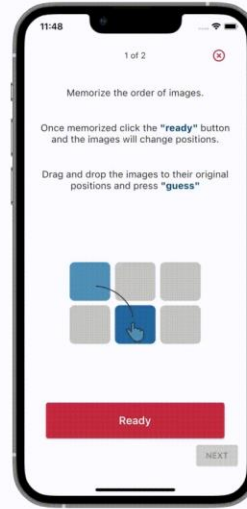
# Patient Reported Data (PRO)

- Informed Consent
- Questionnaires / Surveys
- Ecological Momentary Assessment (EMA)
- Image Capture
- Audio Recording
- Video Recording

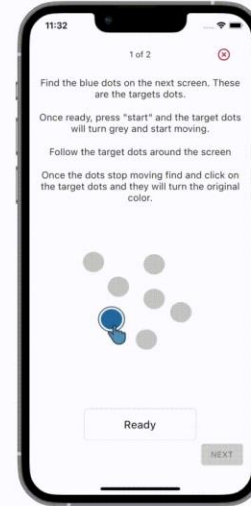


# Cognition

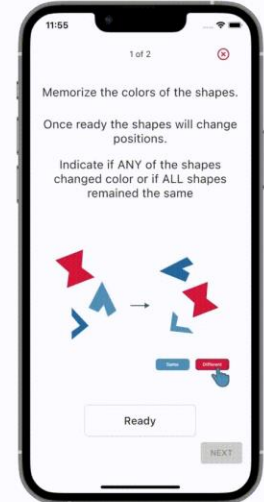
- 14 validated gold-standard cognitive tests
- 8 Neurocognitive domains
  - Sensation
  - Perception
  - Motor skills and construction
  - Attention and concentration
  - Memory
  - Executive functioning
  - Processing speed
  - Language and verbal skills



Picture  
Sequence  
Memory



Multiple Object  
Tracking



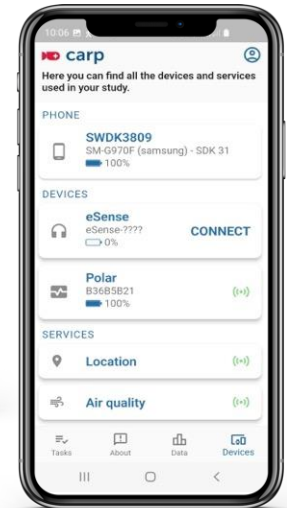
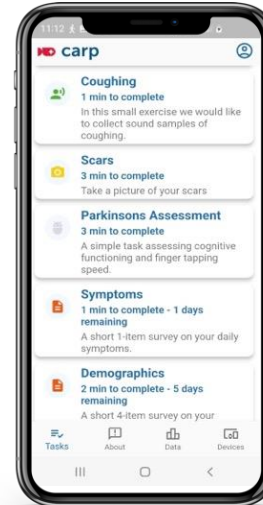
Visual Array  
Change





# “CARP Studies” App (standard, out-of-the box)

- Triggering of **user tasks**
  - surveys, cognitive tests, EMAs, ...
  - notifications
- **Sensor** data collection
  - on-board mobile sensing
  - wearable devices
- Informed Consent (**eConsent**)
- On-going study **information**
- **Internationalization** (DA, EN, ES, FR, ...)
- **Cross-platform** (Android & iOS)
- Infrastructure-independent (**upload** data to any backend server)
- **Available** in Apple & Google App Stores



# Clinical Outcome Assessment / Digital Biomarker

11:13 100% 5G

4 of 4

Do you, or have you, ever smoked (including e-cigarettes)?

(Choose one option)

☐ Never smoked

☐ Ex-smoker

☒ Current smoker (less than once a day)

☐ Current smoker (1-10 cigarettes pr day)

☐ Current smoker (11-20 cigarettes pr day)

☐ Current smoker (21+ cigarettes pr day)

☐ Prefer not to say

Next


11:12 100% 5G

2 of 3

Each card has 5 arrows on it.

Swipe the cards in the direction of the middle arrow on each card.

Ignore all other arrows on the cards, they are only there to distract you



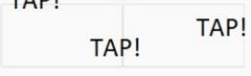
Ready

Next

11:12 100% 5G

3 of 3

After a 3 second countdown, which will appear on screen, tap the two buttons as many times as possible with your index and middle finger, for 10 seconds.



Ready

Next

# Clinical Outcome Assessment / Digital Biomarker

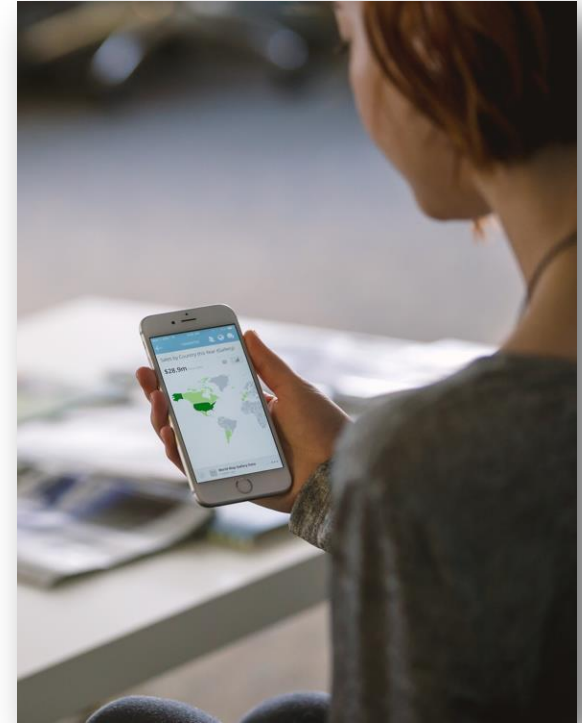
**Table 2.** Hypothetical example of assessing hand function using a smart phone<sup>a</sup>.

Concept being measured	Type of measure
Tasking a study participant to complete a structured tapping exercise on the smart phone for measuring location of the tap and time delays between taps for identifying signal for an early sign of a neurological disorder	Digital biomarker
Tasking a study participant to complete a structured tapping exercise on the smart phone for measuring the study participant's functional ability	COA – Performance outcome
Physical function questionnaire that asks a study participant about hand-related activities of daily living	COA – Patient-reported outcome
Clinician observing a study participant complete a hand exercise and grading the participant's performance	COA – Clinician-reported outcome
Life partner reporting observations of spouse doing certain hand-related functions	COA – Observer-reported outcome

<sup>a</sup>These are theoretical examples. The authors do not assert that hand tapping would be a measure of hand function/dexterity without appropriate evaluation of the analytical and clinical evidence.

# Digital Phenotyping in Neuroscience

- #1 MONARCA** – Digital Biomarkers in Bipolar Disorder
- #2 ICAT** – Internet-based Cognitive Assessment
- #3 Neuropathy Tracker** – Assessment of Neuropathy



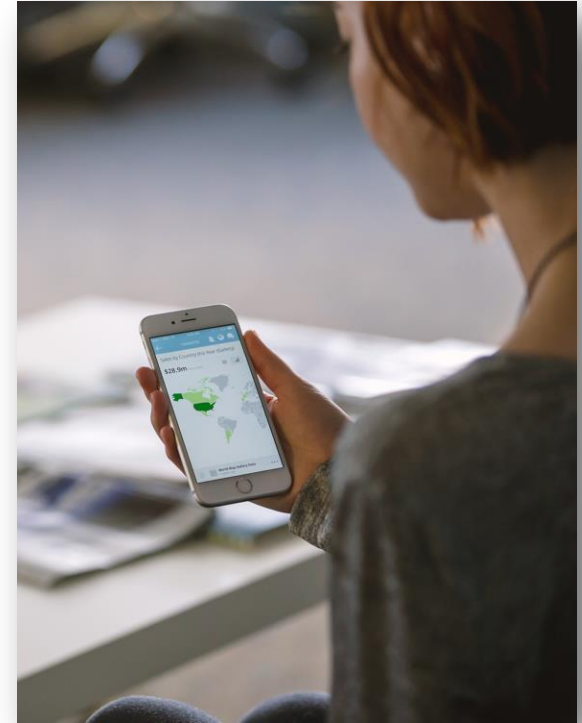


# Digital Phenotyping in Neuroscience

**#1 MONARCA** – Digital Biomarkers in Bipolar Disorder

**#2 ICAT** – Internet-based Cognitive Assessment

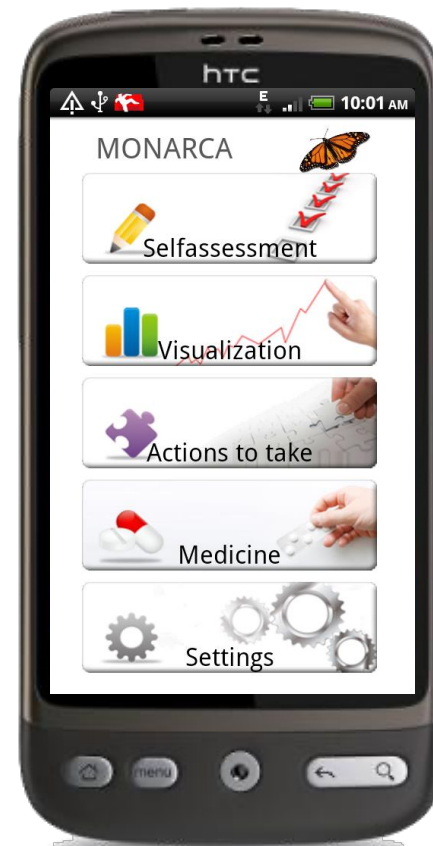
**#3 Neuropathy Tracker** – Assessment of Neuropathy



# 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



Bardram, J. E., Frost, M., Szántó, K., Faurholt-Jepsen, M., Vinberg, M., & Kessing, L. V. (2013, April). Designing mobile health technology for bipolar disorder: a field trial of the MONARCA system. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 2627-2636).

# 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.

# Clinical Validation

## Clinical STUDY

- N=61 | 6 m | 19 m
- HDRS-17 (depression) and YMRS (manic)
- 400+ clinical ratings (monthly)

## RESULTS

- significant correlations between smartphone data and clinical ratings on both HDRS-17 and YMRS
- especially when grouped into 'affective states' (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<sup>a</sup> collected using smartphones and depressive and manic symptoms measured using the HDRS-17 and YMRS, respectively<sup>b</sup>

	Unadjusted			Adjusted <sup>c</sup>		
	Coefficient	95% CI	p-value	Coefficient	95% CI	p-value
<b>Mood (scale: -3 to +3)</b>						
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
<b>Sleep (hours/night)</b>						
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
<b>Activity (no./day)</b>						
Asymptomatic versus mania	-0.037	-0.053 to -0.020	<0.001	-0.042	-0.059 to -0.025	<0.001
Asymptomatic versus hypomania	-0.047	0.022–0.072	<0.001	0.048	0.023–0.072	<0.001
Asymptomatic versus moderate to severe depression	0.047	0.029–0.065	<0.001	0.046	0.027–0.064	<0.001
Asymptomatic versus hypomania	0.012	-0.013 to 0.033	0.34	0.012	-0.013 to 0.037	0.35

<sup>a</sup>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.

<sup>b</sup>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.

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

	Unadjusted			Adjusted <sup>d</sup>		
	Coefficient	95% CI	p-value	Coefficient	95% CI	p-value
<b>Incoming calls (no./day)</b>						
Asymptomatic versus mania	0.95	0.076–1.82	0.033	0.97	0.10–1.84	0.029
<b>Duration incoming calls (sec/day)</b>						
Asymptomatic versus hypomania	729.51	334.87–1124.13	<0.001	768.10	374.34–1161.86	<0.001
<b>Outgoing calls (no./day)</b>						
Asymptomatic versus hypomania	2.09	0.39–3.80	0.016	2.08	0.37–3.80	0.017
<b>Duration outgoing calls (sec/day)</b>						
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
<b>Outgoing text messages (no./day)</b>						
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.

<sup>a</sup>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.

<sup>b</sup>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.

<sup>c</sup>Analyses including all study participants; total N = 61.

<sup>d</sup>Adjusted for age and sex.

# Classification Affective Disorders from Mobility Patterns

- 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 entropy

**“Mobility patterns derived from mobile location data are a promising digital diagnostic marker in discriminating between patients with BD and UD.”**

Table 3  
Classification

	PPV <sup>d</sup>	NPV <sup>c</sup>	AUC <sup>f</sup>
BD vs. BD, euthymic state	0.65 (0.03)	0.70 (0.02)	0.75 (0.02)
BD vs. BD, depressive state	0.78 (0.04)	0.65 (0.06)	0.81 (0.03)
UD, depressive state vs. BD, depressive state	0.70 (0.07)	0.77 (0.07)	0.79 (0.05)

<sup>a</sup> 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.

<sup>b</sup> Sensitivity = true positive / positive.

<sup>c</sup> Specificity = true negative / negative.

<sup>d</sup> Positive predictive value.

<sup>e</sup> Negative predictive value.

<sup>f</sup> Area under the curve.

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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) and YMRS (mania)
- openSMILE (emolarge)

Classification results

- depressive state : 77%
- manic state : 75%
- HC vs. bipolar : 79%

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

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.

OPEN

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

Jepsen et al.  
*International Journal of Bipolar Disorders*  
doi:10.1186/s40345-021-00243-3

International Journal of  
Bipolar Disorders

RESEARCH

Open Access

Voice analyses using smartphone-based data in patients with bipolar disorder, unaffected relatives and healthy control individuals, and during different affective states

Maria Faurholt-Jepsen<sup>1,2</sup>, Darius Adam Rohani<sup>3</sup>, Jonas Busk<sup>4</sup>, Maj Vinberg<sup>1</sup>, Jakob Eyvind Bardram<sup>1</sup> and Lars Vedel Kessing<sup>1</sup>

## 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  $n = 40,041$ , and HC  $n = 20,298$ ). Daily, patients evaluated symptoms using a smartphone-based system. Affective states were defined according to these evaluations. Data were analysed using random forest machine learning algorithms.  
**Results:** Compared to HC, BD was classified with a sensitivity of 0.76 (SD 0.11)/AUC = 0.76 (SD 0.11) and UR with a sensitivity of 0.51 (SD 0.21)/AUC = 0.52 (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

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<sup>1</sup>Marie Faurholt-Jepsen and Darius Adam Rohani: contributed equally to this work and are shared first authors  
<sup>2</sup>Copenhagen Affective Disorder Research Center (CADC), Psychiatric Center Copenhagen, Rigshospitalet, Blegdamsvej 3, 2100 Copenhagen, Denmark  
Full list of author information is available at the end of the article

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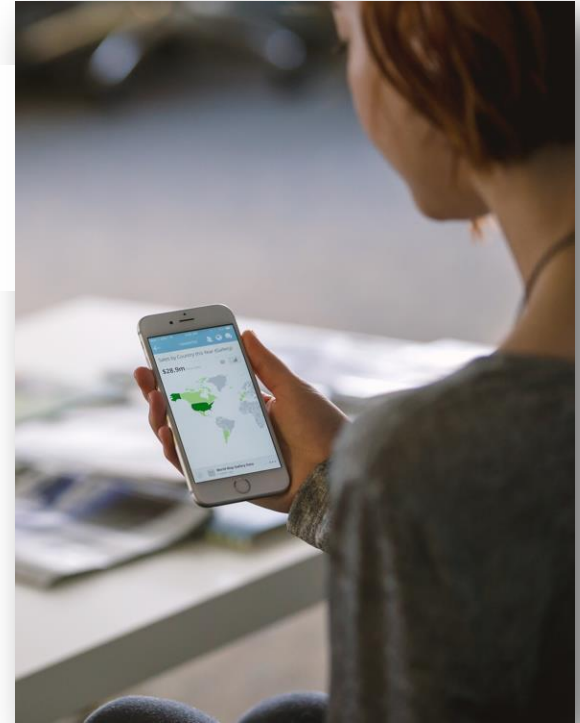
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# Digital Phenotyping in Neuroscience

#1 **MONARCA** – Digital Biomarkers  
in Bipolar Disorder

#2 **ICAT** – Internet-based Cognitive  
Assessment

#3 **Neuropathy Tracker** – Assessment  
of Neuropathy



# ICAT – Internet-based Cognitive Assessment Tool

- Based on the Screen for Cognitive Impairment (**SCIP**) in Psychiatry
  - clinically administered
  - paper-based & manual scoring
- **ICAT Vision**
  - patient self-administered
  - large-scale deployment (national scale)
  - useful across many health domains
- **ICAT Technology**
  - browser-based (scalable)
  - automatic speech recognition & scoring
  - study & participant management using CARP



**Table 1.** Description of the internet-based cognitive assessment tool subtests.

Task features	Task 1: list learning <sup>a</sup>	Task 2: consonant repetition <sup>b</sup>	Task 3: Wechsler Adult Intelligence Scale letter-number sequencing <sup>c</sup>	Task 4: delayed list learning <sup>d</sup>	Task 5: visuomotor tracking <sup>e</sup>
Measure	Verbal memory (immediate recall)	Working memory	Working memory	Delayed verbal memory (delayed recall)	Psychomotor speed
Scoring criteria	Total number of correctly recalled words for 3 trials	Total number of correctly recalled letters	Total number of correctly sorted sequences	Total number of correctly recalled words	Total number of correct matching letters
Score range	0–30	0–24	0–21	0–10	0–30
Practice test	No	No	Yes	No	Yes



Hafiz, P., Miskowiak, K. W., Kessing, L. V., Jespersen, A. E., Obenhausen, K., Gulyas, L., ... & Bardram, J. E. (2019). The internet-based cognitive assessment tool: system design and feasibility study. *JMIR formative research*, 3(3).

# Validation Study

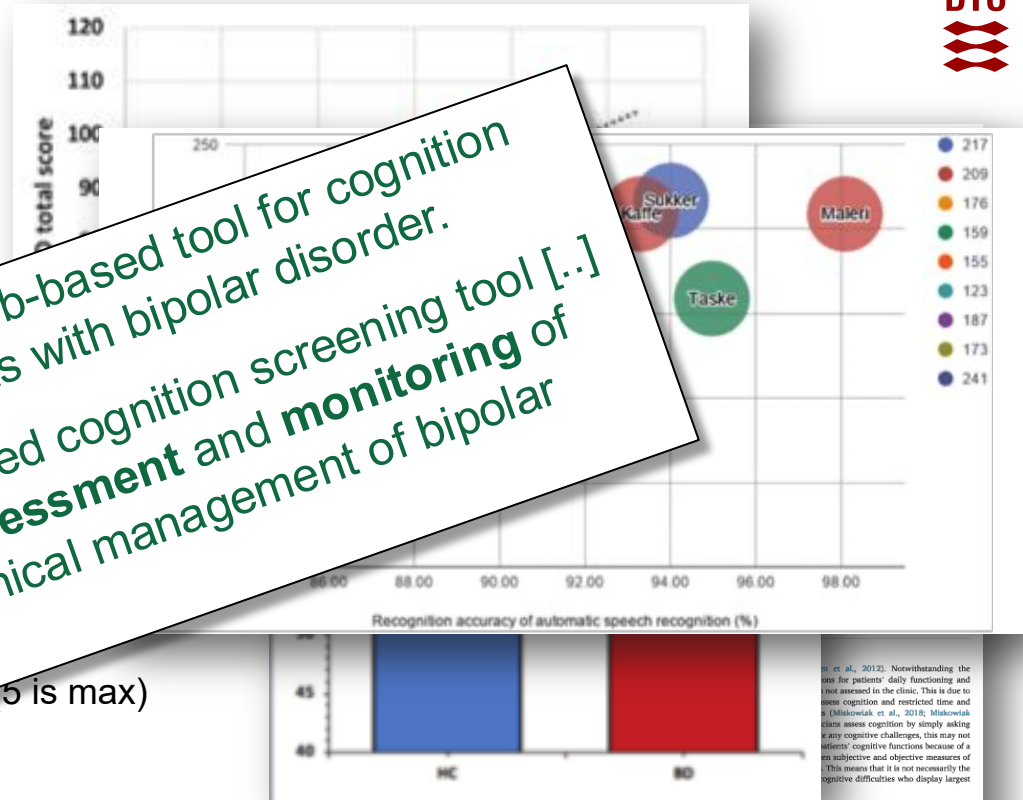
## • Study

- 35 HC | 35 BD
- SCIP vs. ICAT
- in-clinic assessment
- validation | speech

## • Results

- scores :  $p = 0.72$ ,
- speech :  $p = 0.91$ ,
- usability :  $M=4.1$  (Scale 1-5 (5 is max))

“ICAT is a [...] **valid** web-based tool for cognition assessment in patients with bipolar disorder. [...] a novel web-based cognition screening tool [...] for **large-scale assessment** and **monitoring** of cognition in the clinical management of bipolar disorder.”



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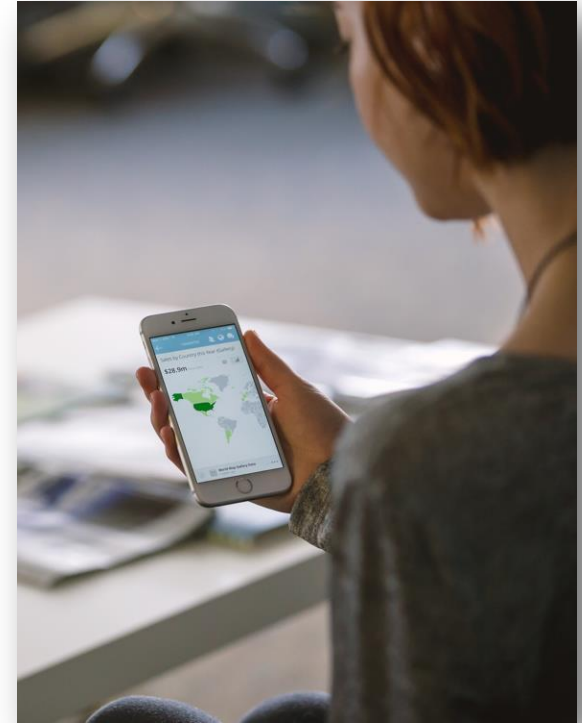
0165-0327/© 2021 The Author(s). Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

et al., 2012). Notwithstanding the data for patients' daily functioning and not assessed in the clinic. This is due to issues of cognition and restricted time and space (Miskowiak et al., 2018; Miskowiak et al., 2019). Miskowiak et al. (2018) assess cognition by simply asking patients to perform any cognitive challenges, this may not reflect patients' cognitive functions because of a lack of subjective and objective measures of cognition. This means that it is not necessarily the cognitive difficulties who display largest

Miskowiak, K. W., Jespersen, A. E., Obenhausen, K., Hafiz, P., Hestbæk, E., Gulyas, L., ... & Bardram, J. E. (2021). Internet-based cognitive assessment tool: sensitivity and validity of a new online cognition screening tool for patients with bipolar disorder. *Journal of Affective Disorders*, 289, 125-134.

# Digital Phenotyping in Neuroscience

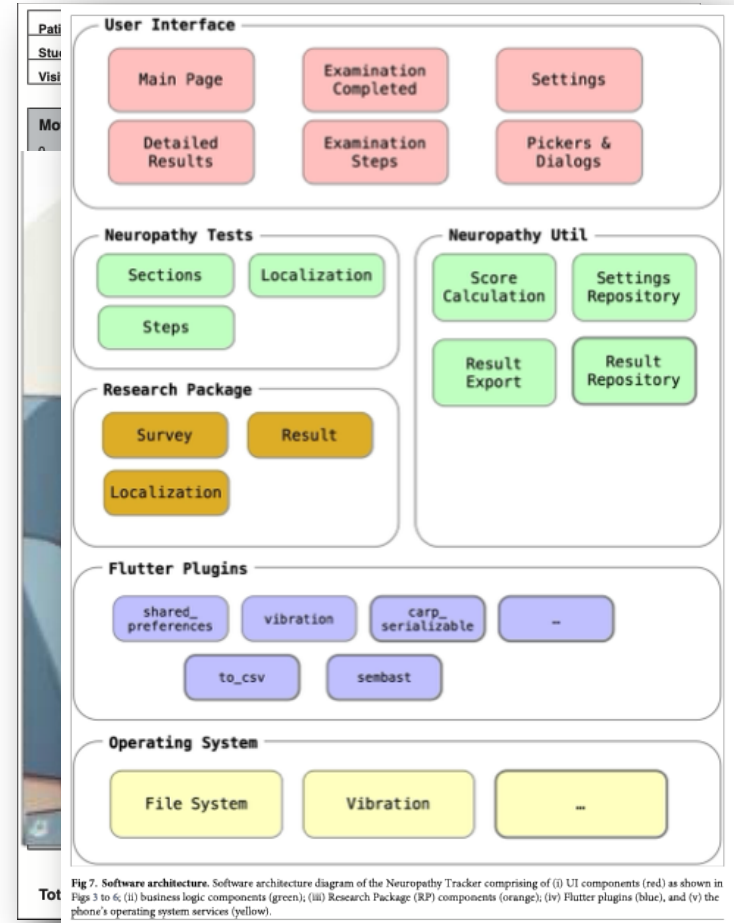
- #1 **MONARCA** – Digital Biomarkers in Bipolar Disorder
- #2 **ICAT** – Internet-based Cognitive Assessment
- #3 **Neuropathy Tracker** – Assessment of Neuropathy



# Neuropathy Tracker

- **Peripheral neuropathy**
  - common complication of diabetes or cancer treatment
  - early detection and treatment are crucial
  - done in the clinic using paper-and-pen tool(s)
- **Vision**
  - patient-administered, “at-home” assessment
  - screening | diagnosis | treatment monitoring
  - early detection
- **Technology**
  - “Custom” designed and implemented using the CARP software components
  - Using patients’ own phones and accessories

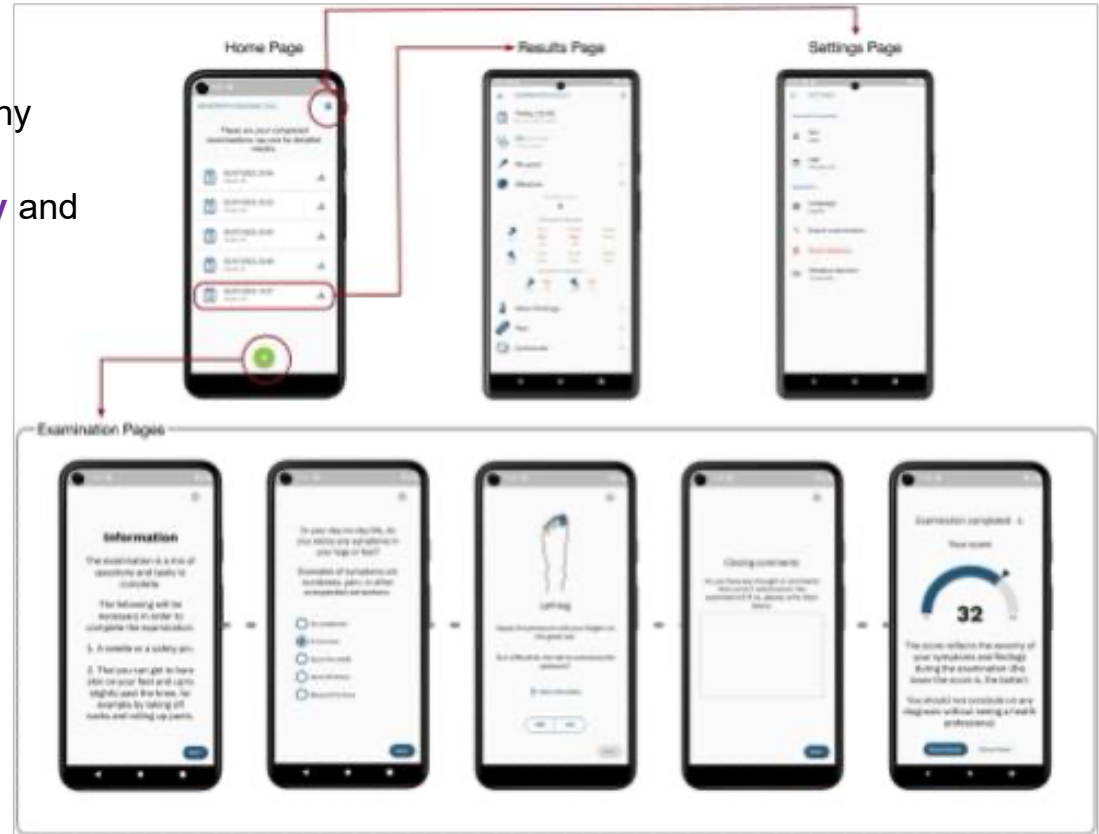
Bardram, J. E., Westermann, M., Makulec, J. G., & Ballegaard, M. (2025). The Neuropathy Tracker—A mobile health application for ambulatory and self-administered assessment of neuropathy. *PLOS Digital Health*, 4(2).





# User-Centered Design

- involving neurologists, patients, and healthy subjects
- ensuring a high degree of **clinical validity** and **usability**



Bardram, J. E., Westermann, M., Makulec, J. G., & Ballegaard, M. (2025). The Neuropathy Tracker—A mobile health application for ambulatory and self-administered assessment of neuropathy. *PLOS Digital Health*, 4(2).

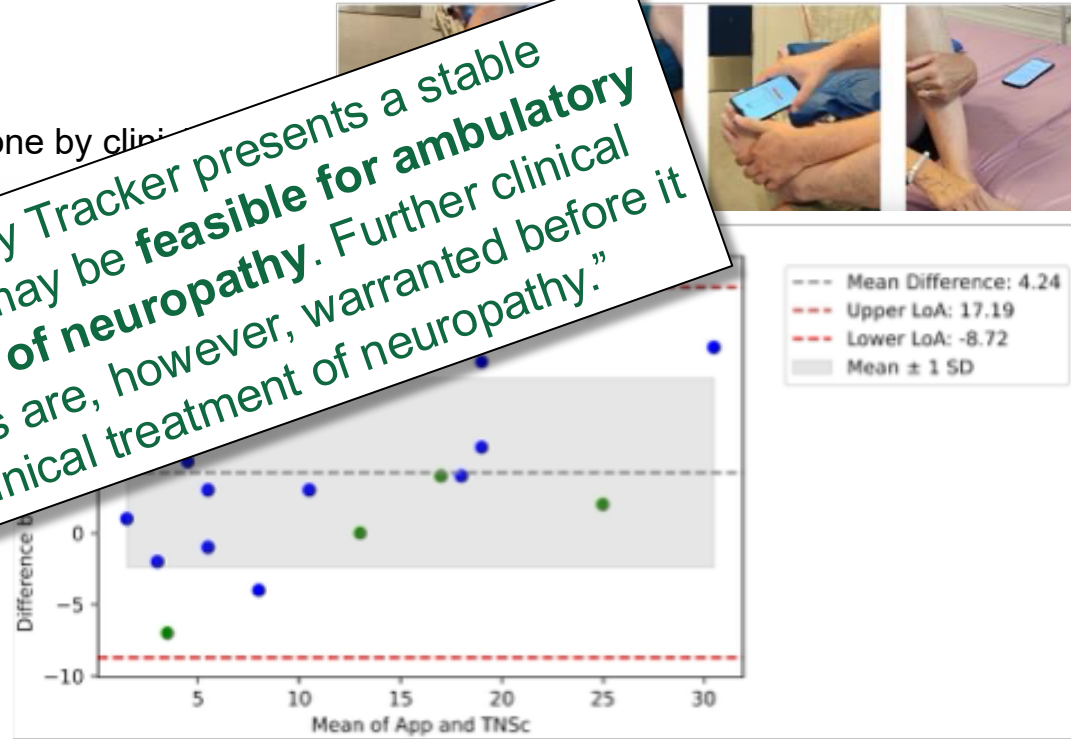
# Feasibility Study

- Comparing to “Golden Standard”
  - Total Neuropathy Score clinical (TNSc) done by clinician
- N=17 neuropathy patients
- Self-assessment in the clinic

## Results

- $\rho = 0.86$ ,  $p < 0.001$
- Bland-Altman Plot

“The [...] Neuropathy Tracker presents a stable mHealth tool that may be **feasible for ambulatory self-assessment of neuropathy**. Further clinical validation studies are, however, warranted before it is used in the clinical treatment of neuropathy.”

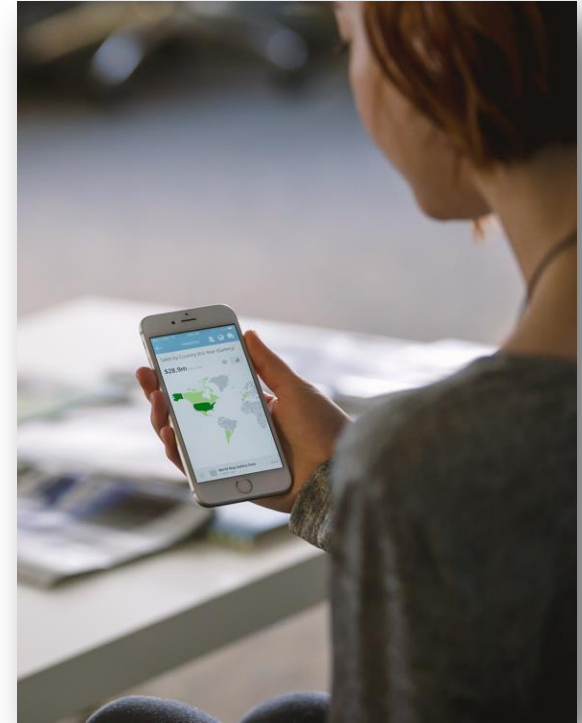


**Fig 10. Concurrent validity.** A Bland-Altman plot with the differences between the Neuropathy Tracker (“App”) and TNSc measures on the y-axis and their means on the x-axis. The plot includes horizontal lines for the mean difference and the limits of agreement (LoA) and is color-coded by sex (green = male, blue = female).

Bardram, J. E., Westermann, M., Makulec, J. G., & Ballegaard, M. (2025). The Neuropathy Tracker—A mobile health application for ambulatory and self-administered assessment of neuropathy. *PLOS Digital Health*, 4(2).

# Digital Phenotyping in Neuroscience

- #1 MONARCA** – Digital Biomarkers in Bipolar Disorder
- #2 ICAT** – Internet-based Cognitive Assessment
- #3 Neuropathy Tracker** – Assessment of Neuropathy





Interested in **Digital Phenotyping** and  
using CARP as part of a research project?

Just reach out...

# Questions?

## Funding Acknowledgement

