



Data driven digital mental health promotion & disease prevention

26. Österreichische Gesundheitsförderungskonferenz des Fonds Gesundes Österreich

Villach, 12 June 2024

Prof. dr. Heleen Riper
Vrije Universiteit, Amsterdam





EAT TOGETHER
 Foodsharing Volksküche
 Essen für ALLE

Montag - Freitag
 von 10:00 - 14:00

Machen wir
 die Welt
 lebenswerter

♥
 WIR
 KOCHEN
 MIT
 GERETTETEN
 LEBENS MITTELN



Kein Mittagessen mehr
 verpassen?
 Holde Mitter als die
 mit der Eat Together Multi App Channel
 QR-Code scannen
 Channel abonnieren
 Glocke aktivieren

RADFESTIVAL AM
 WÜRTHERSEE
 SAMSTAG
 03.09.2022
 START DER RADPARADEN
 10:00 bis 12:00 Uhr
 12:00 bis 14:00 Uhr
 14:00 bis 16:00 Uhr
 16:00 bis 18:00 Uhr
 18:00 bis 20:00 Uhr
 20:00 bis 22:00 Uhr

ist die
 post
 mit
 W
 100
 Frisch und mit
 LIEBE GEGART!



How familiar are you with digital interventions?

Unguided
(asynchronous)



Guided
(asynchronous)

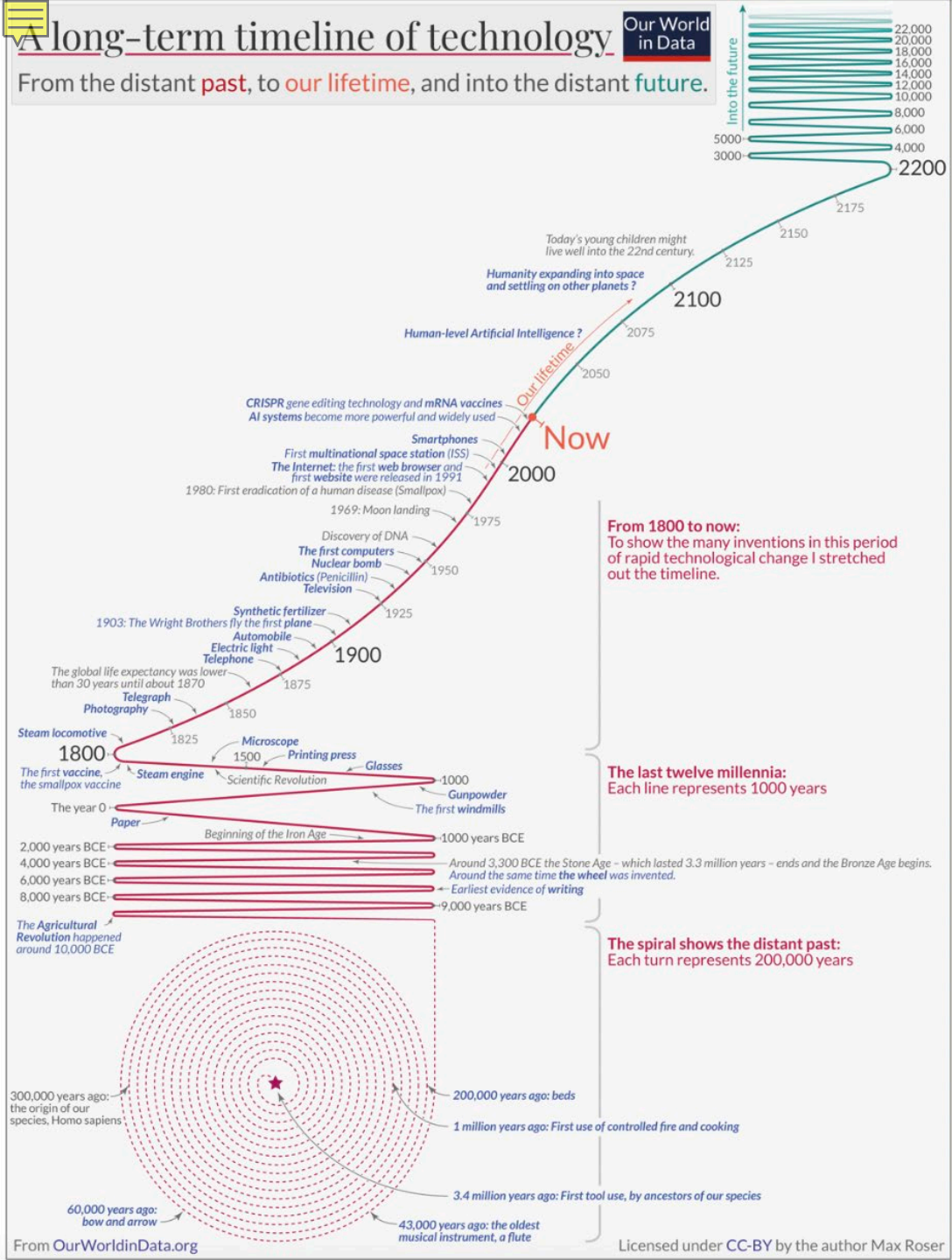


Blended (asynchronous
and synchronic)



Videoconferencing
(synchronic home or clinic)





Technology changes extraordinarily fast

For the good and the bad

Human-Level AI?

Max Roser, 2023

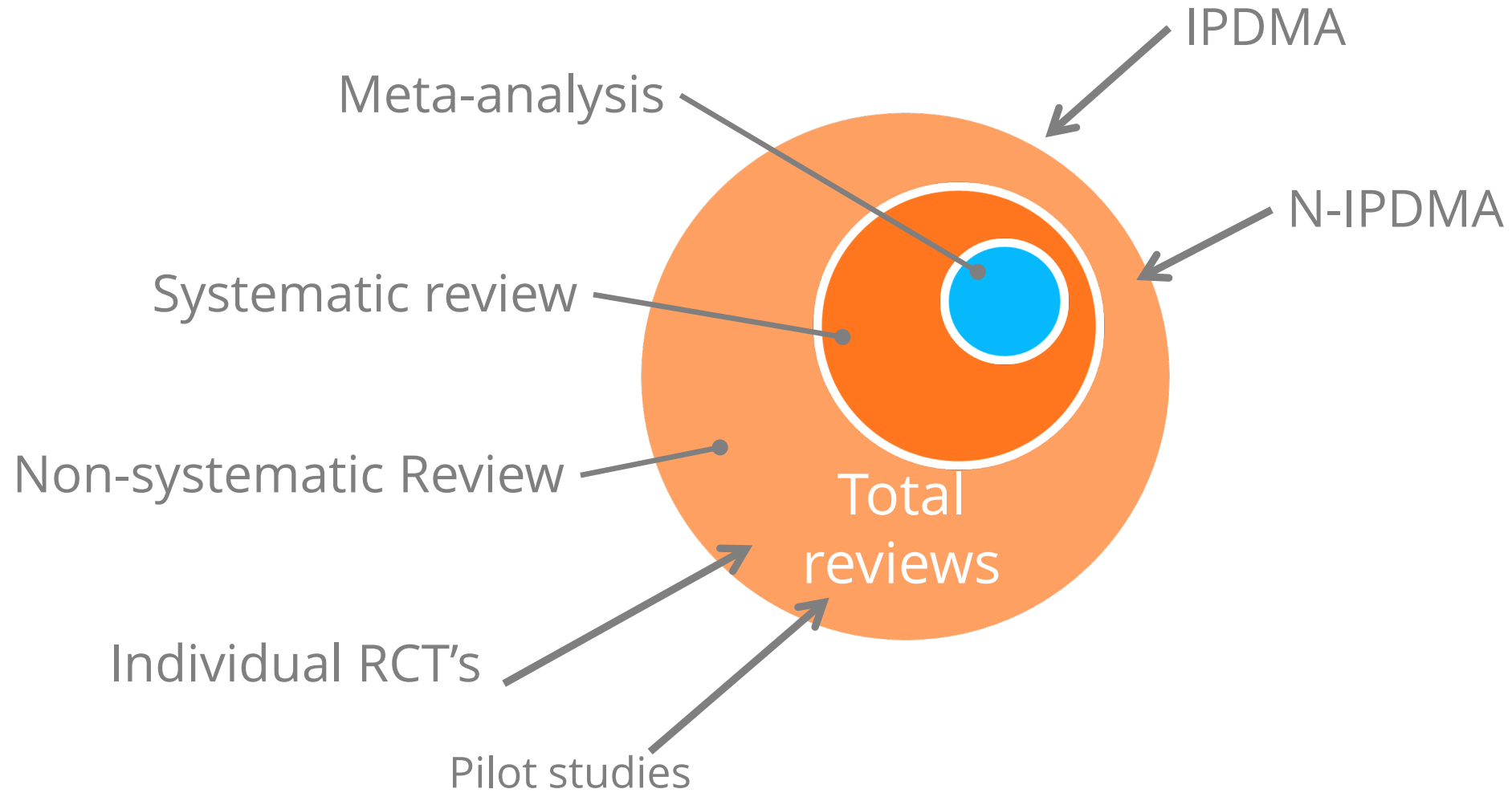
Start 3,4 million years ago



Why data driven digital mental health promotion & disease prevention?

- To create and implement evidence based digital mental health promotion interventions
- Randomized controlled trials and meta-analytics : golden standard
- Realworld data & realworld evidence

Levels of Evidence



25 years Digital Mental & Behavioural Health

2000 - 2004

Development of internet-based interventions

2006 Stockholm

ISRII: Assessing **clinical effectiveness** (RCT)

2007 Charlottesville

Cost-effectiveness studies and implementation

2009 Amsterdam

Globalization & Digital **Ecological Momentary Assessment**

2011 Sydney

Beyond CBT, meta-analyses

2013 Chicago

Micro interventions, Individual Patient Data Meta-Analysis

2014 Valencia

Serious Gaming

2016 Seattle

Youth

2017 Berlin

Mobile health & EMA

2019 Auckland

AI & ML & Sensoring, **digital phenotyping**

2022 Pittsburgh

AI & Just In Time Adaptive Interventions

Wright et al. (2023) Interventions with Digital Tools for Mental Health Promotion among 11–18 Year Olds: A Systematic Review and Meta-Analysis. (Anxiety)

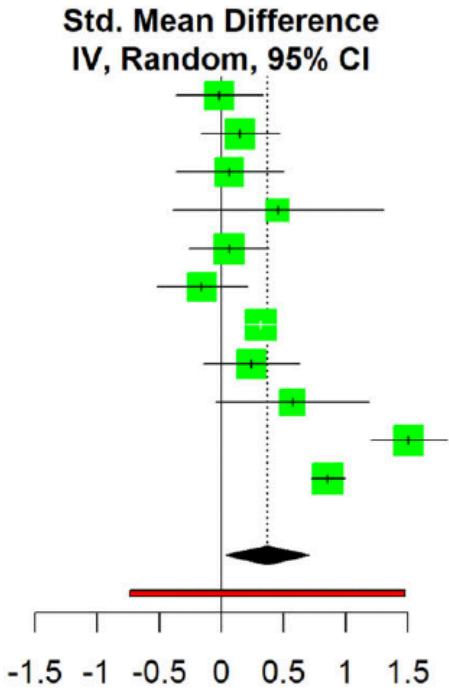
N = 27 studies (13,216 participants): mental health literacy, well-being, (help-seeking behavior, stress management, relaxation, mindfulness, resilience and positive psychology.

**Small sign. Effects
Anxiety, well-being,
protective factors**

- **School & support**
- **High = more**

Study	Experimental			Control			Weight	SMD	95% CI
	Mean	SD	Total	Mean	SD	Total			
Calear et al., 2016	4.65	4.12	79	4.56	4.96	52	9.4%	-0.02	[-0.37; 0.33]
Egan et al., 2021	1.85	0.95	73	1.99	0.90	81	9.6%	0.15	[-0.17; 0.47]
Kauer et al., 2012	9.80	9.30	50	10.40	9.60	35	8.8%	0.06	[-0.37; 0.50]
Malboeuf-Hurtubise et al., 2021	2.87	0.83	11	3.50	1.70	11	5.8%	0.45	[-0.40; 1.30]
Manicavasagar et al., 2014	6.38	7.26	62	6.86	8.61	92	9.6%	0.06	[-0.26; 0.38]
O’Dea et al., 2020	9.78	4.20	55	9.12	4.15	60	9.3%	-0.16	[-0.52; 0.21]
O’Dea et al., 2021	4.21	4.78	400	5.82	5.33	878	10.6%	0.31	[0.19; 0.43]
Osborn et al., 2020	7.92	4.48	50	9.00	4.45	53	9.1%	0.24	[-0.15; 0.63]
Perkins et al., 2021	10.99	5.61	21	14.58	6.70	21	7.4%	0.57	[-0.05; 1.19]
Schleider et al., 2020	18.83	0.75	106	19.95	0.73	105	9.7%	1.51	[1.20; 1.81]
Zheng et al., 2021	3.49	0.33	467	3.79	0.37	429	10.6%	0.86	[0.72; 0.99]
Total (95% CI)			1374			1817	100.0%	0.37	[0.04; 0.70]
Prediction interval									[-0.73; 1.47]

Heterogeneity: Tau² = 0.2151; Chi² = 115.34, df = 10 (P < 0.01); I² = 91%

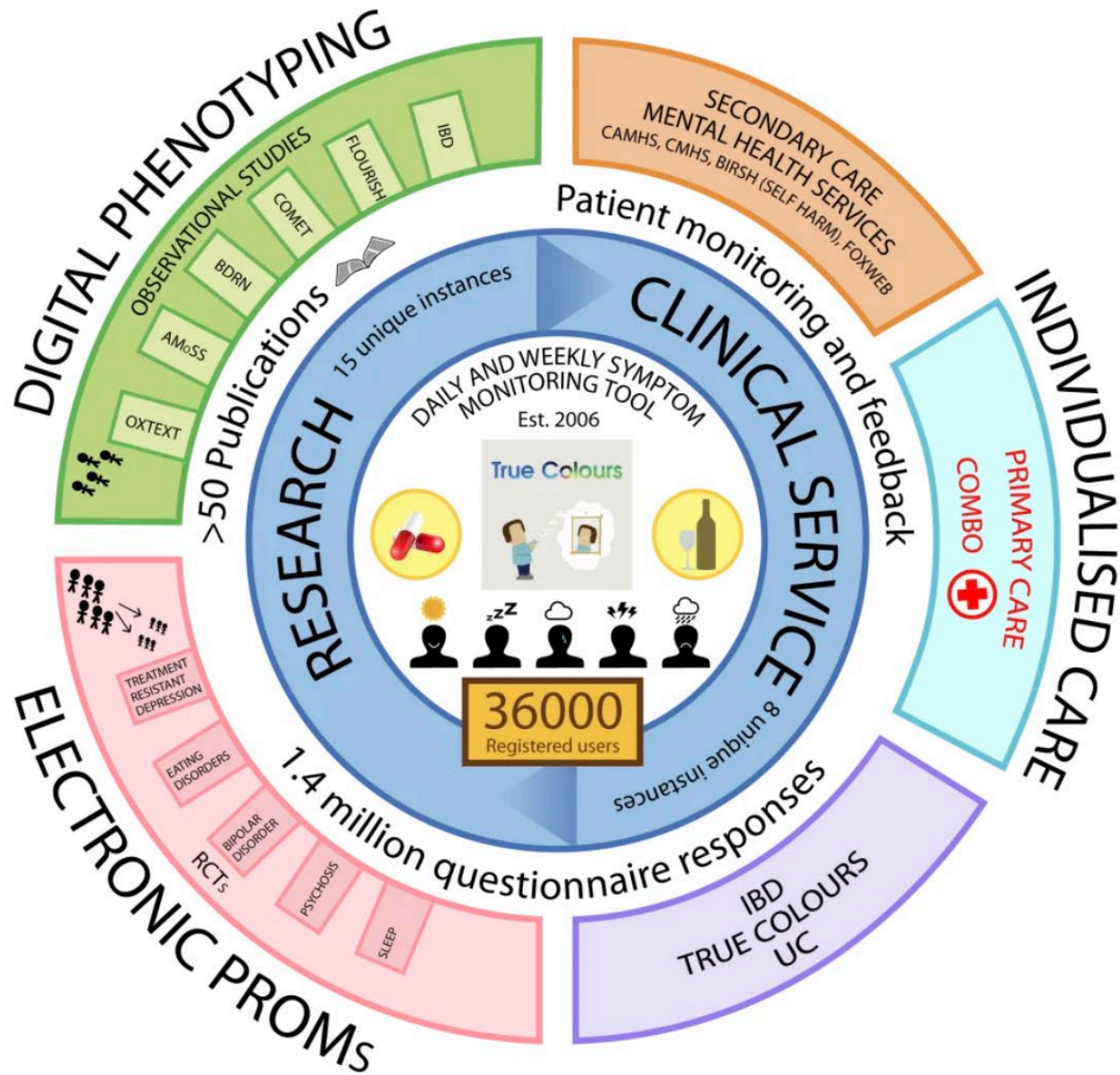


Difference between digital mental health promotion & universal & selected prevention not always clear cut

Twenty-five years of digital mental health:

From platform development, feasibility and assessment of effective mental health promotion towards

User-centred, Personalized Prediction models for Monitoring and Prevention and Treatment supported by (generative) AI & JITAIs



TRUE
COLOURS?

Dr. Ropin?

2009 start

Goody et al. (2020) The True Colours Remote Symptom Monitoring System: A Decade of Evolution. JMIR



EMA

- Mood and behaviours change over **time**
- **Context** of mood and behaviour manifestations is important
- Large differences between people (**heterogeneity**)
- Retrospective assessment
 - Recall bias
 - Over generalization
 - Peak end rule

Patient Health Questionnaire (PHQ-9)				
Over the <u>last 2 weeks</u> , how often have you been bothered by any of the following problems?	Not at all	Several days	More than half the days	Nearly every day
• Little interest or pleasure in doing things	0	1	2	3
• Feeling down, depressed, or hopeless	0	1	2	3
• Trouble falling or staying asleep, or sleeping too much	0	1	2	3
• Feeling tired or having little energy	0	1	2	3
• Poor appetite or overeating	0	1	2	3

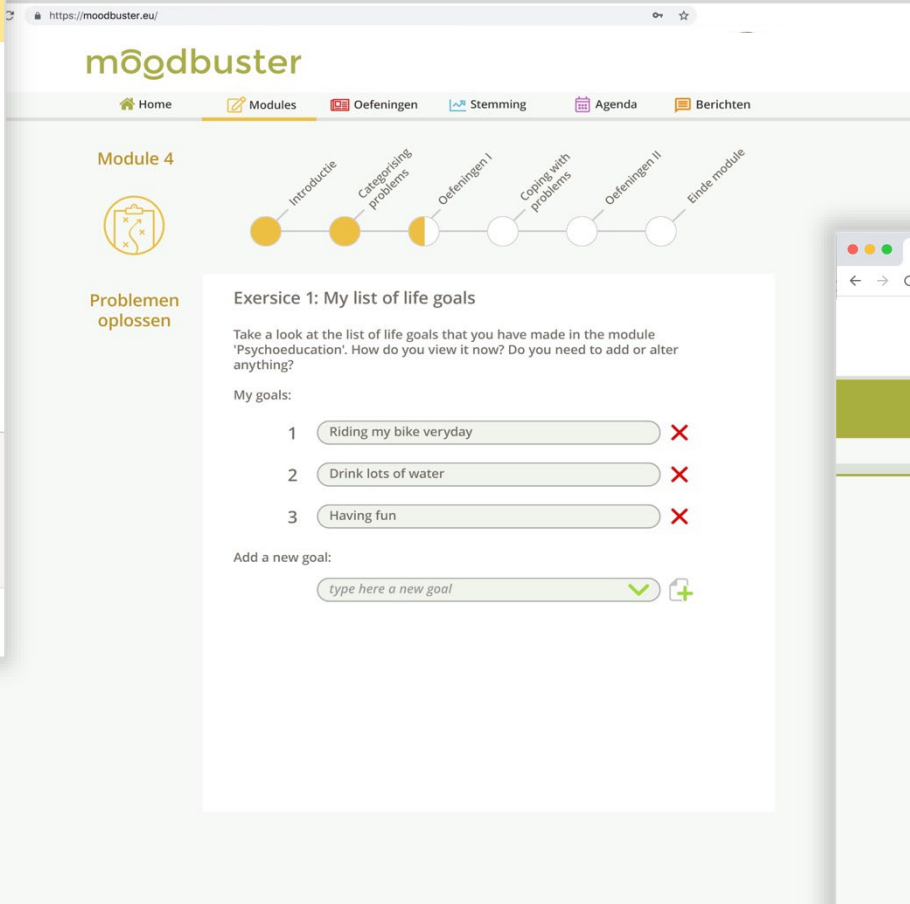
MoodBuster 2.0



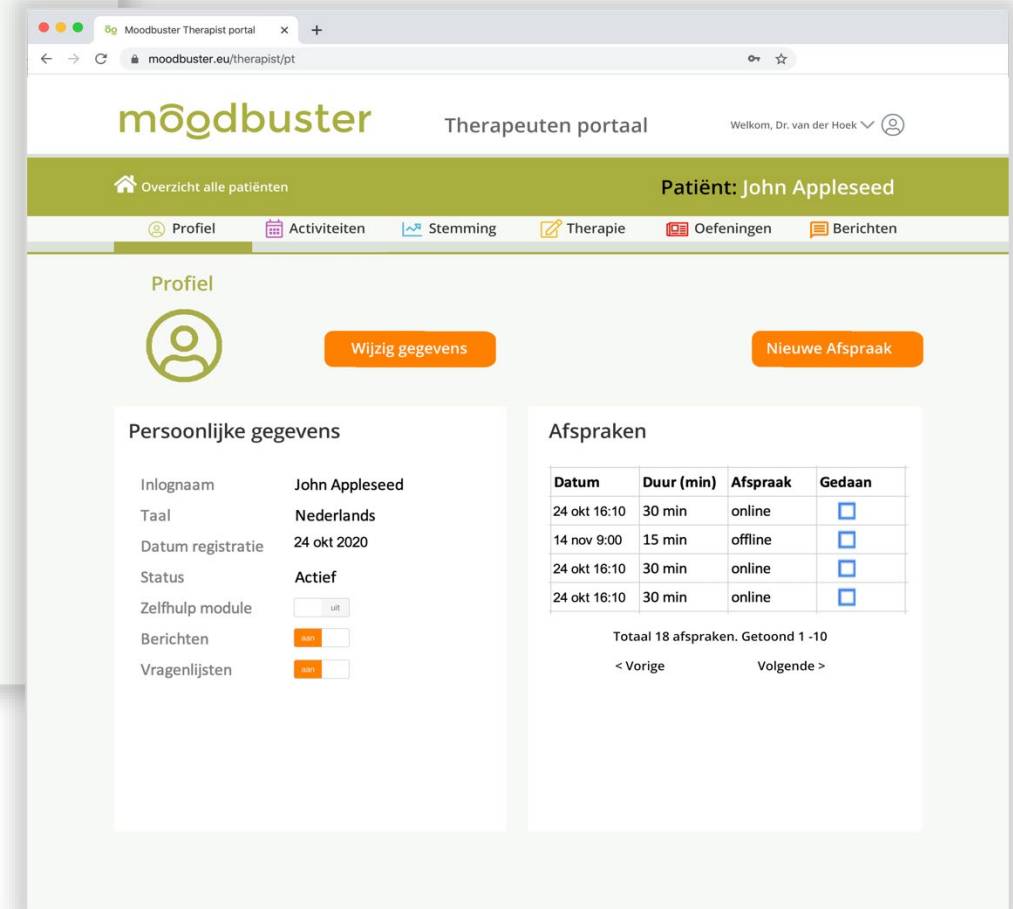
Content Management System



Mobile App



Patients' Portal



Therapists' Portal

VU University, Amsterdam &
INESC TEC, Porto & UL, Limerick



Digital Phenotyping

"The moment-by-moment quantification of the **individual-level human phenotype** in situ using passive and/or active data from personal digital devices, in particular smartphones and sensors."

"**It** also makes use of wearable sensors that capture real-time physiological data, social media fora or interactions with others captured via call and text logs."

"**Data obtained** may be viewed as a proxies for underlying states of behavior, emotion, cognition and environment."

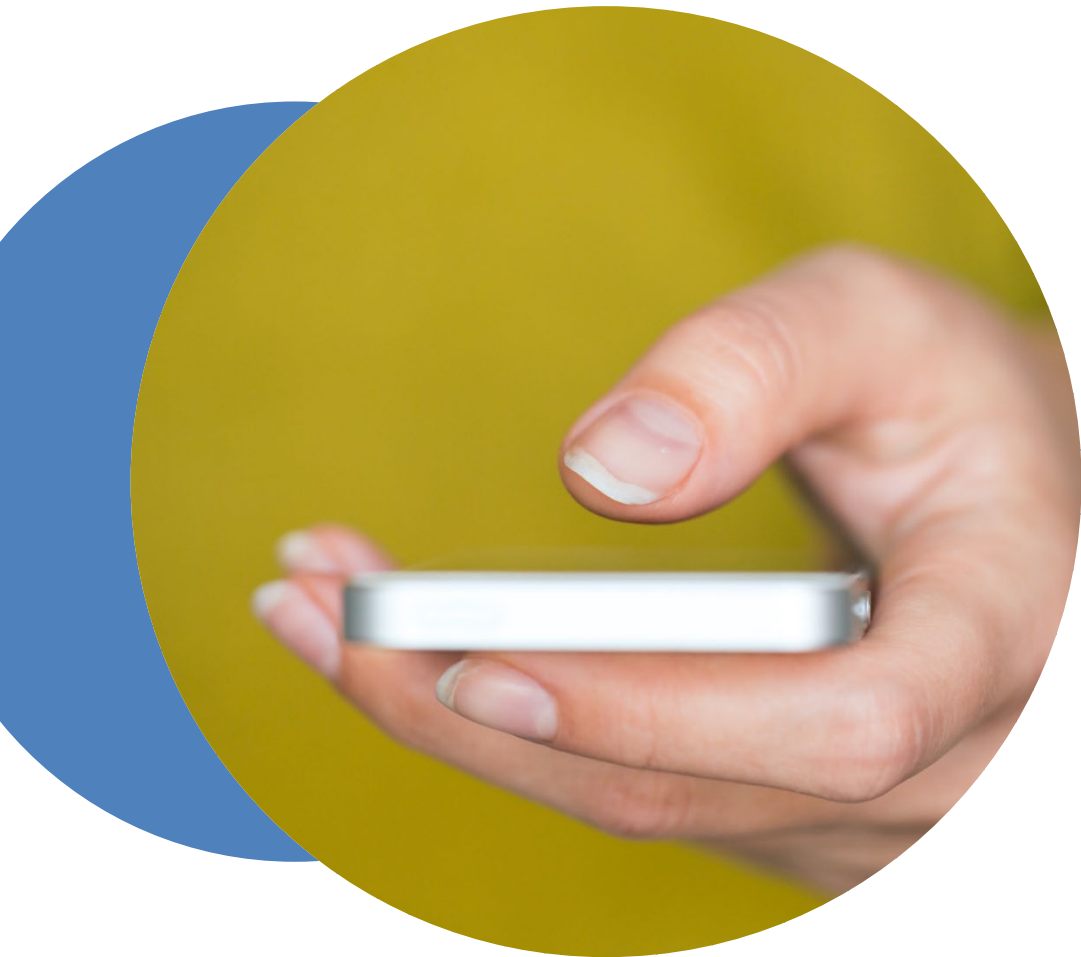
Change of the way how we understand mental health and addictive disorders which are correlated with new means of live data collection

(Onnela 2015, Jain 2015, Torous 2018)

"From communication & intervention towards Real time monitoring & JITAIs"

*Psychological
Physiological
Behavioural
Environment*





AIMS

- to obtain “objective” markers in addition to self-report, interviews, physical exams, biological markers and brain imaging data
- Examples physiology (heart rate); cognition (e.g. screen use), behavioural (e.g., global positioning system) and social (e.g., call frequency)
- *to increase insights into the temporal dynamics of our health and behaviour*
- predict and prevent onset or relapse

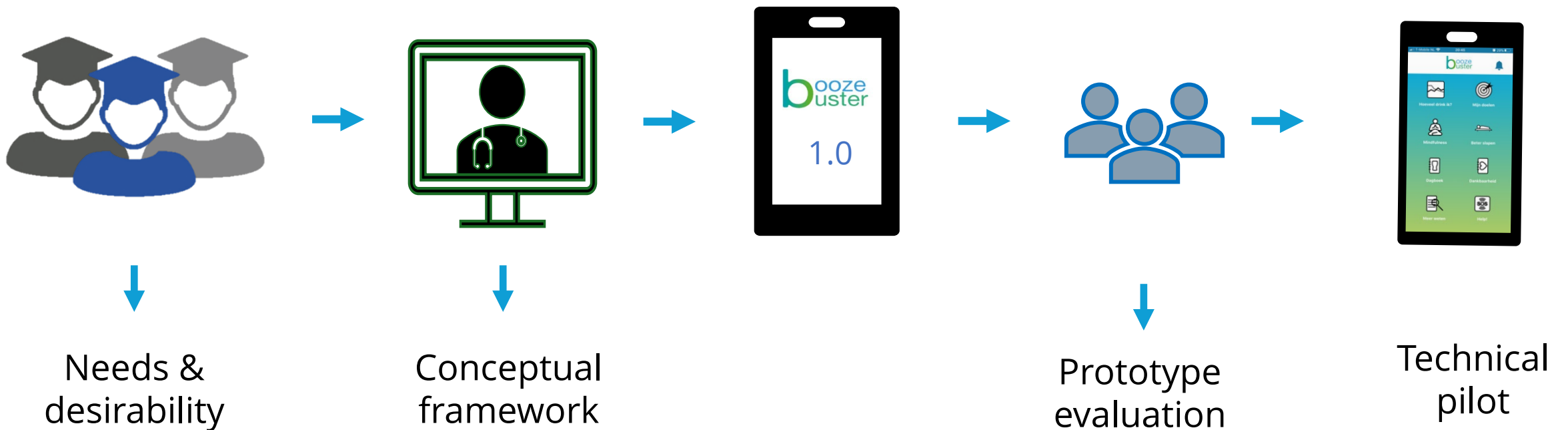
examples

- to classify mood states on the basis of activity patterns (Mohr et al. 2011)
- quantification of realworld social networks through Bluetooth signals
- keyboard touch & speed (Insell 2018)

Boozebuster Smartphone Intervention to Reduce Young Adults' Alcohol Consumption **Indirect Recruitment & Intervention**

Development

Schulte, Boumparis Riper (2022). Frontiers in Digital Health



Health Promotion Approach Boozebuster N = 503



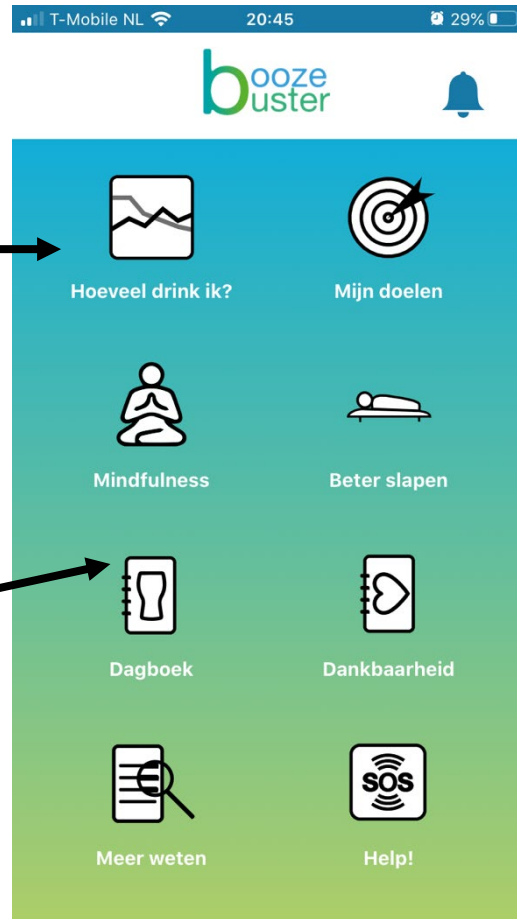
Dagboek

Stemming

Slaap

Hoeveel drankjes heb je gisteren gehad?

Registreer



EMA

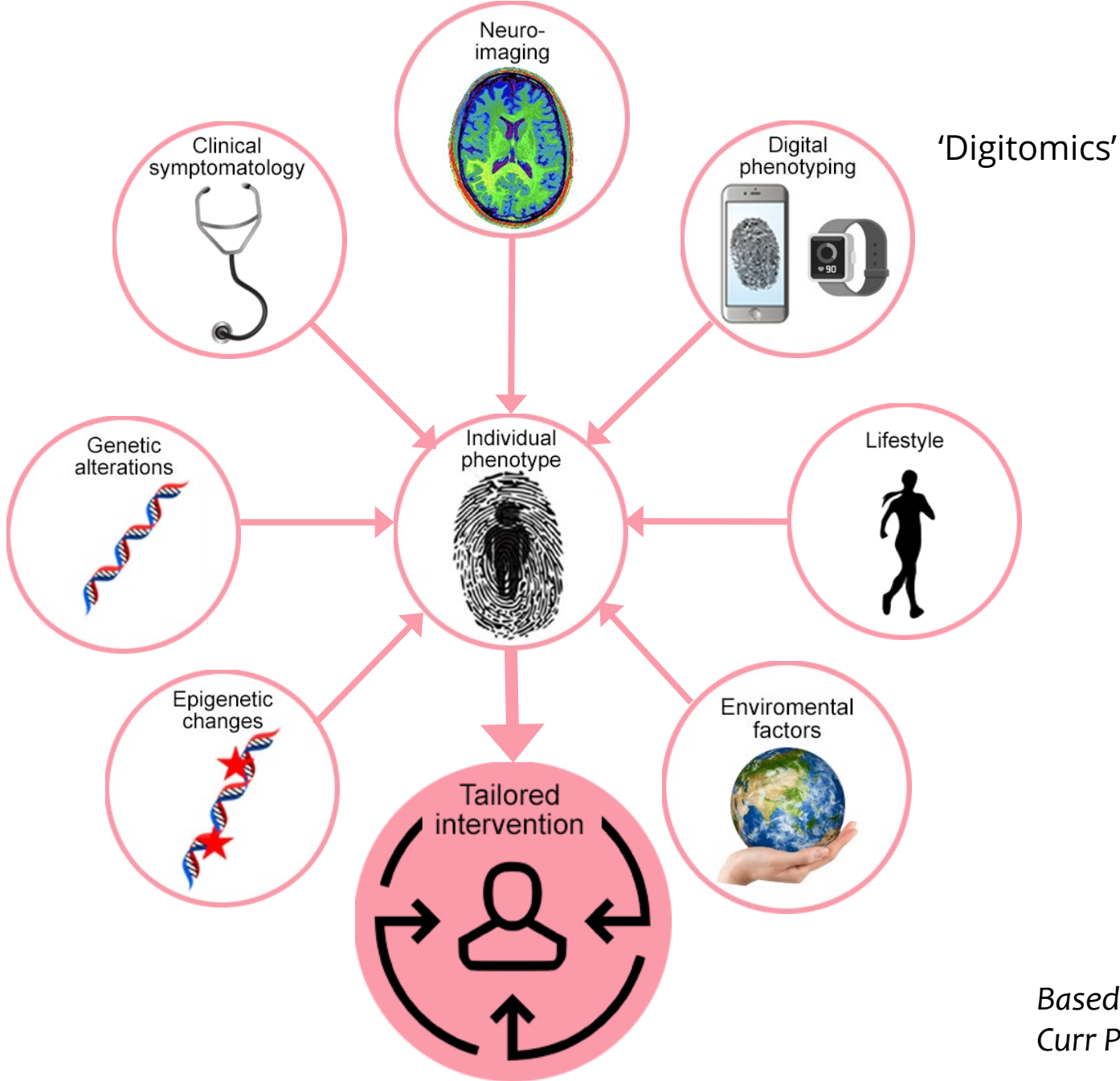


- Results independent of analyses
- Exp v minimal active
 - Both groups decreased AC/ NS
 - ITT vs. Per protocol vs. Study completers
 - Binge drinkers vs. problem drinkers
 - RCQ: moderator

DATA Driven

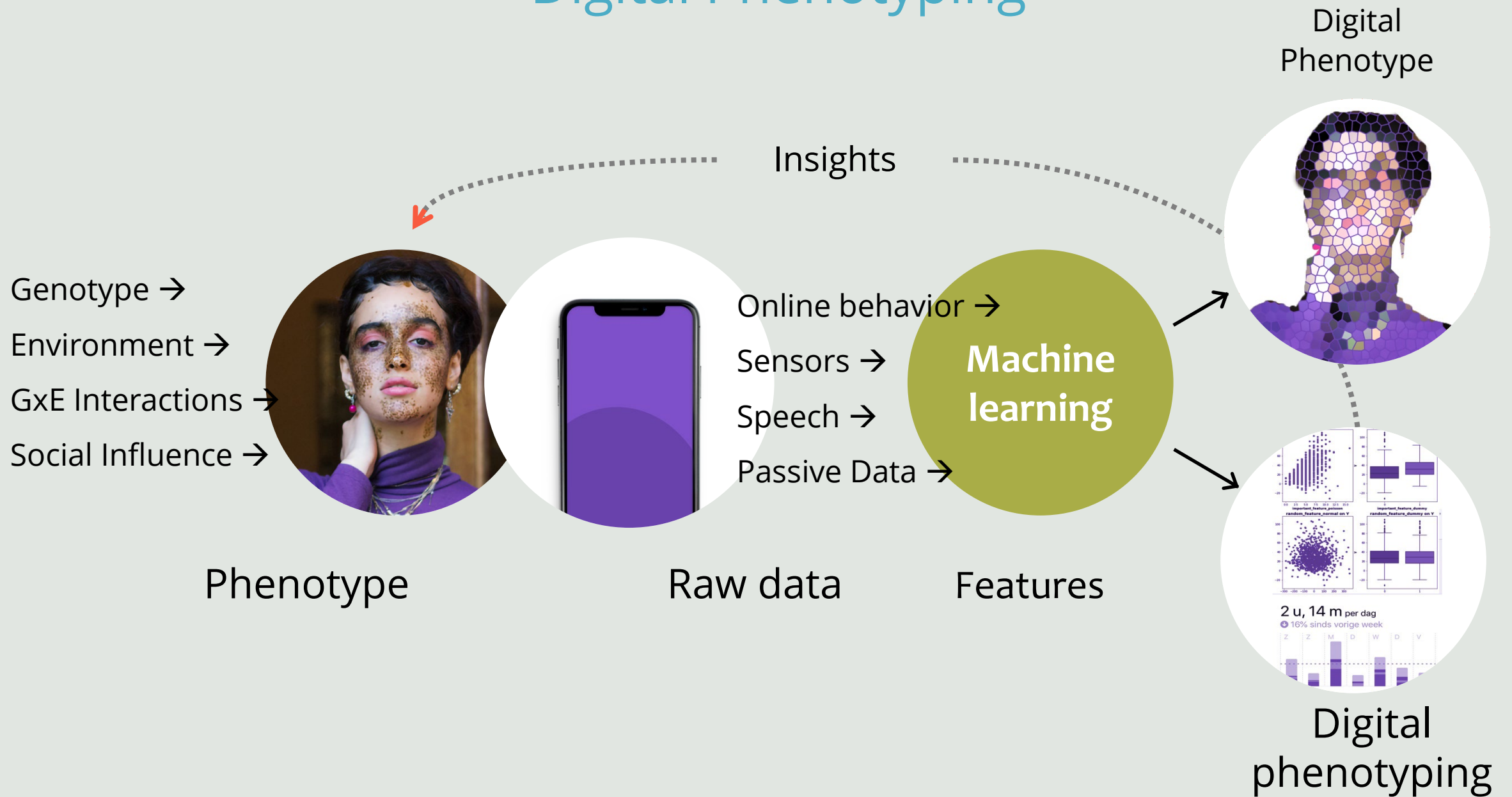


Personalised therapy



Based on Barrigon et al.
Curr Psychiatry Rep (2019)

Digital Phenotyping



Example: Combined Active and Passive EMA

- E-COMPARED DATA
 - 5 EU countries
 - N = 143 patients
 - 9 -425 days of EMA data.
- Active & passive EMA
5 countries
2018

Description of the pre-processed input features.

Input feature	Description
<i>Base features</i>	
EMA mood ratings	Averages of the patients daily mood ratings
Additional mood ratings	Indicates whether patient rated mood more than two times (more than the protocol requires) per day
Nationality	The country of origin of the patient
Module completions	Whether a therapeutic module has been completed
Treatment state	The current treatment state of the patient: can be active (before finishing the final module), done (after having finished the final module but still able to access the system) and archived (no longer having access to the system)
Day of the week	Current day of the week
Number of answered questions per day	Number of questions the patient rated a day
<i>Extended features</i>	
EMA ratings	Averages of patients daily EMA ratings (except mood)
Number of treatment days	Total number of days in the treatment
Number of exchanged messages with therapist	The number of messages that have been sent by the therapist
Number of exchanged characters with therapist	The number of characters contained in the messages exchanged with the therapist
Number of messages	Number of feedback messages generated by the MoodBuster application (motivational messages and reminders)
Number of patient messages	Number of messages sent by the patient
Number of web sessions	Number of web sessions
Number of pages in module	The number of pages viewed in the modules
Mood Response time	The response time to an EMA request to rate the mood
Module duration	Duration of the current module since the patient started



Predicting short term mood developments among depressed patients using adherence and ecological momentary assessment data

Adam Mikus^a, Mark Hoogendoorn^{a,*}, Artur Rocha^b, Joao Gama^c, Jeroen Ruwaard^d, Heleen Riper^d



Results

a.

AI perspective

**Best of 3
prediction
models**

b.

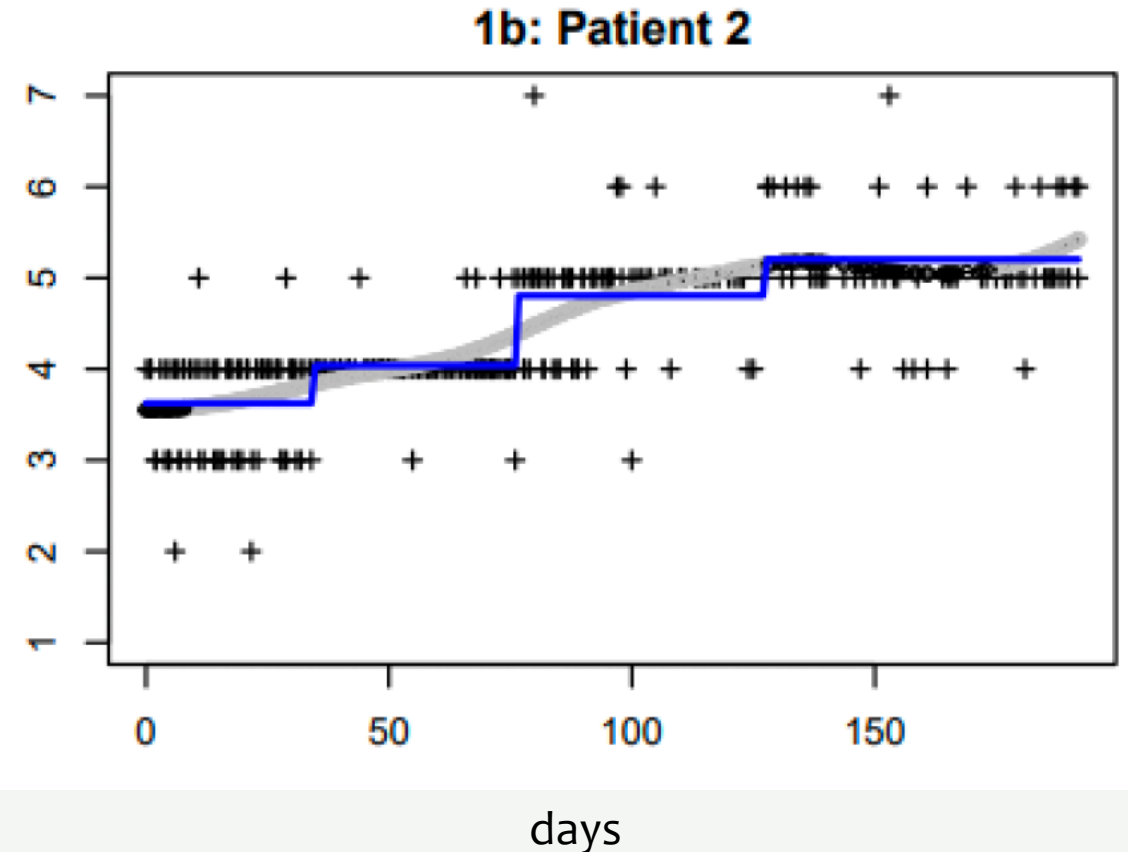
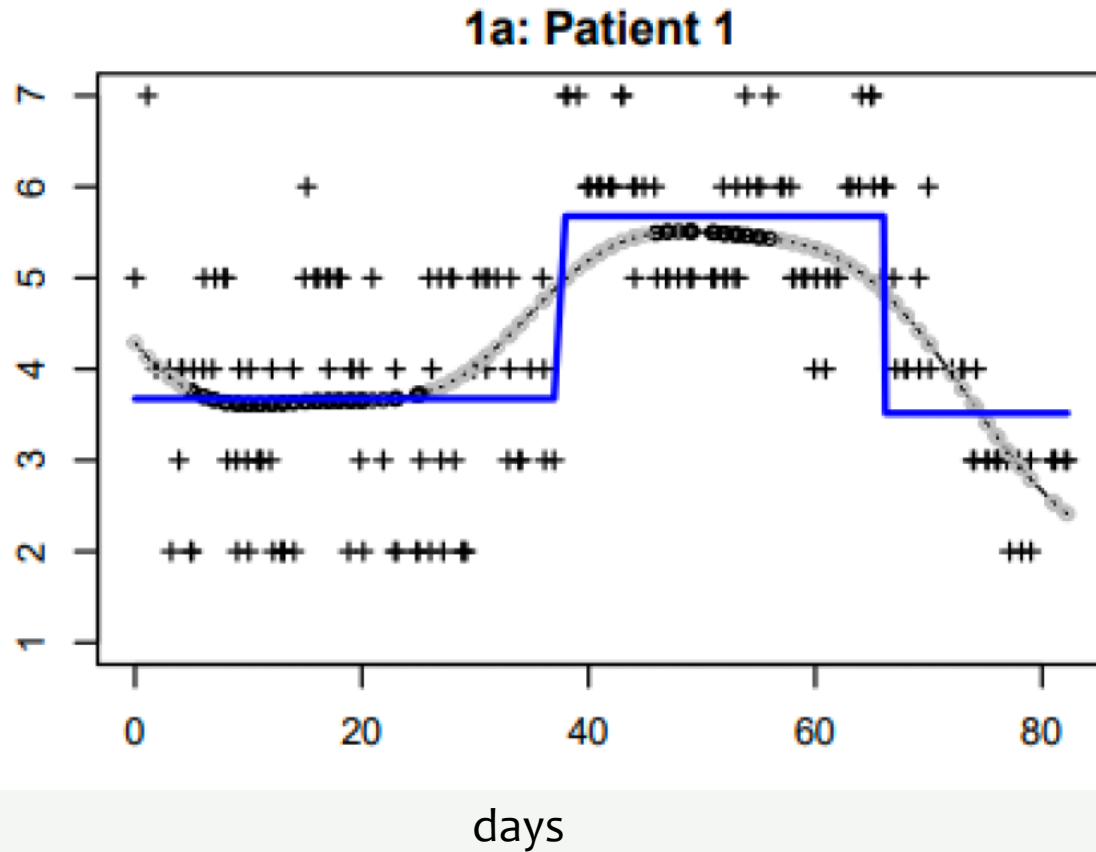
- **Active past EMA mood most influential (A)**
- **adherence & usage data did not improve prediction accuracy (P)**

Results of best predictive models (note: mood has been scaled between 0 and 1, and the RMSE should also be interpreted on that scale).

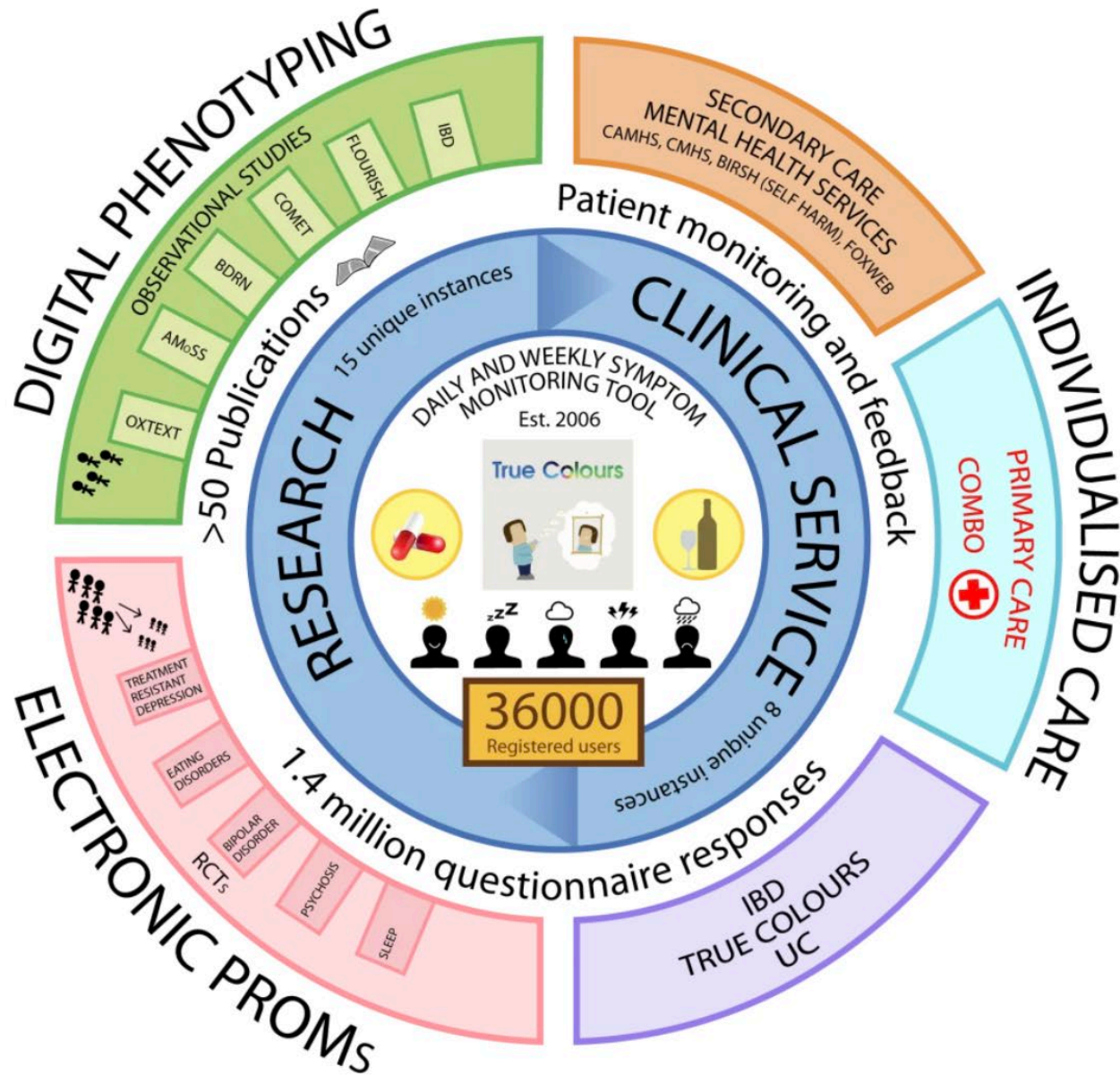
Set-up	Best model	RMSE result (standard deviation)
<i>Regular input</i>		
Single	GRU 2 layer/GRUP	0.070 (0.00)
Clustered	GRUP	0.066 (0.023)
Individual	LSTMP	0.086 (0.047)
<i>Extended input</i>		
Single	LSTM 1 layer/ LSTMP	0.070 (0.00)
Clustered	GRUP	0.075 (0.026)

Figure 1.

Plot of SI EMA data for each participant with estimated long-term trends.



- 3 times a day SI
- sudden & gradual changes



TRUE COLOURS

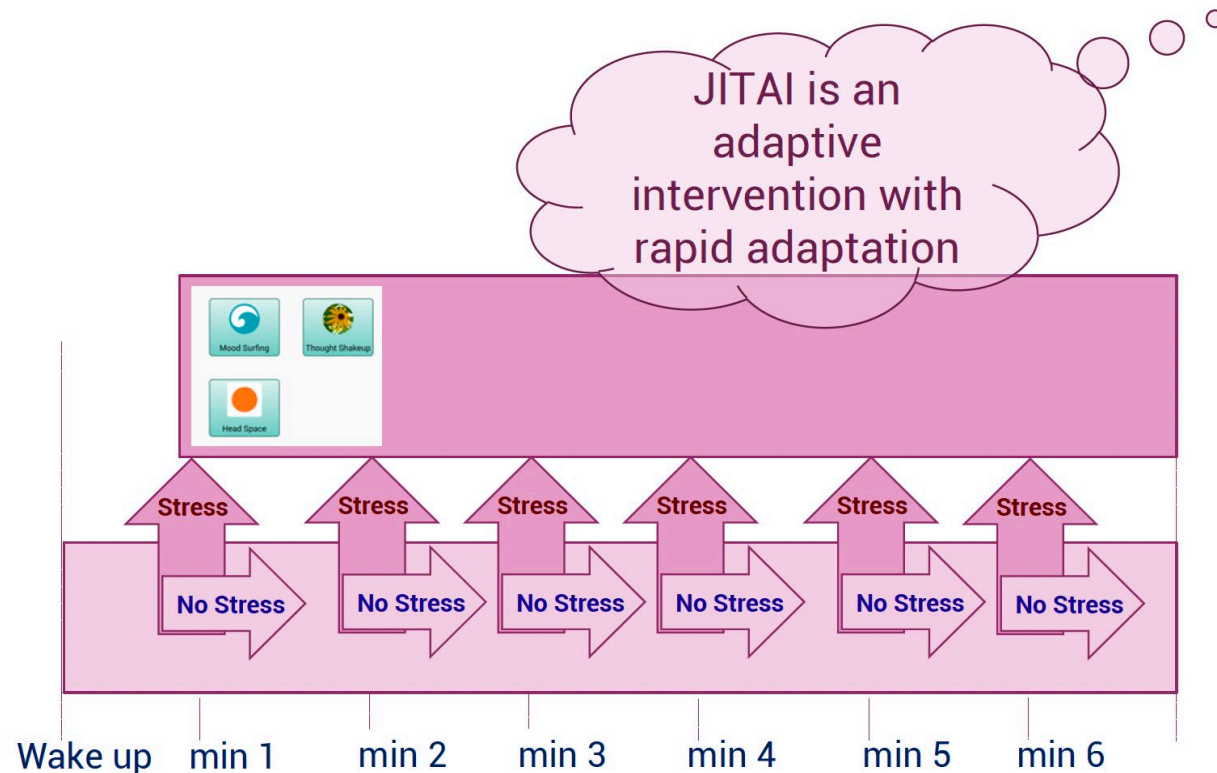
BD & BPD

Goody et al. (2020) The True Colours Remote Symptom Monitoring System: A Decade of Evolution. JMIR

Mental Health Promotion Data-driven Interventions

New directions

Just-In-Time Adaptive Interventions are smartphone interventions: deliver timely tailored support by adjusting to changes in both internal states and external contexts. No Waste!



What happens in a day?
smoking cessation

Mental Health Promotion Data-driven Interventions

New directions

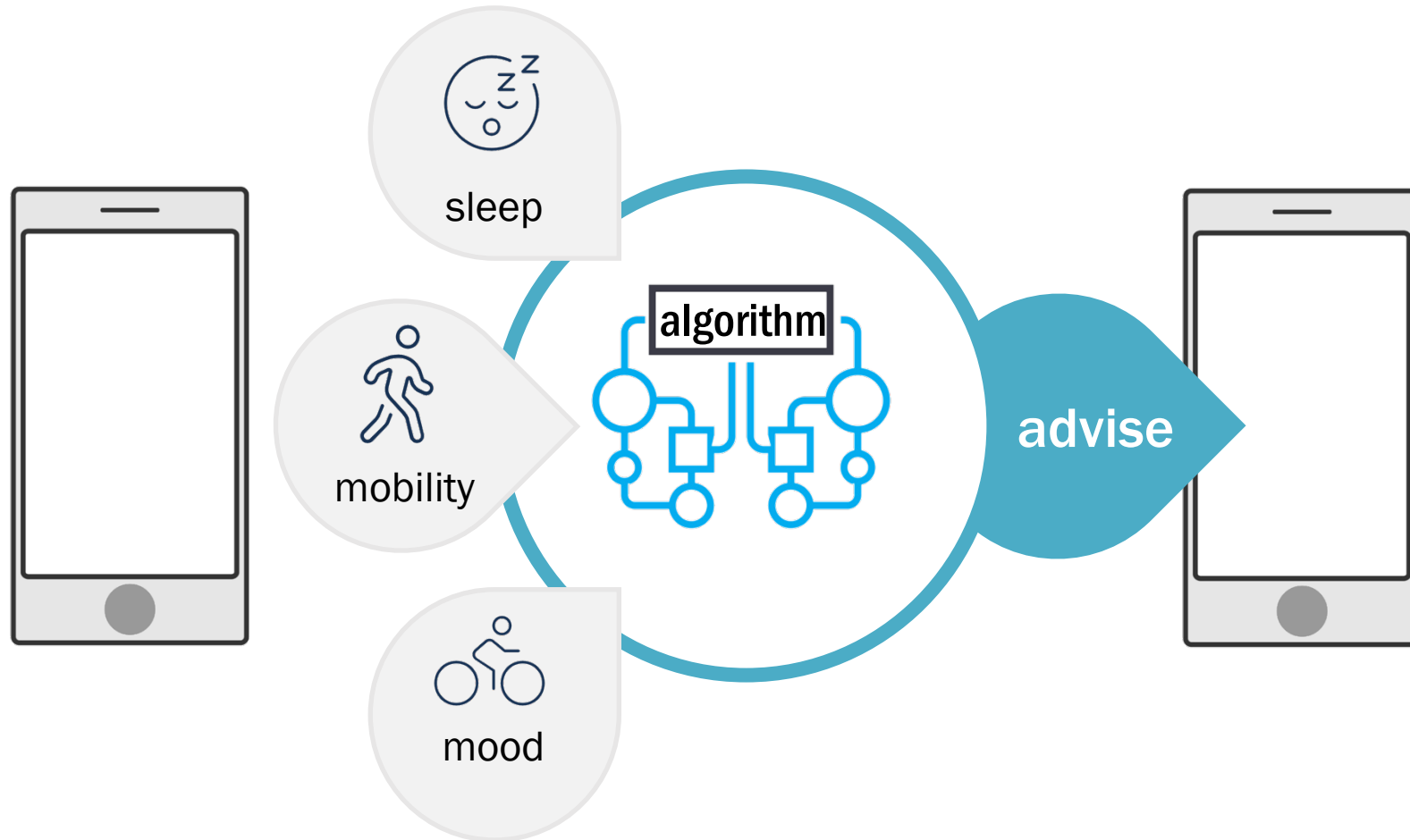
JITAI

Micro Interventions

Single Interventions

Indirect Interventions

Future Challenges



- External validation
- Trust
- Acceptation
- Literacy
- Privacy
- Empowerment
- Self-management
- Implementation
- Reflection & critical appraisal

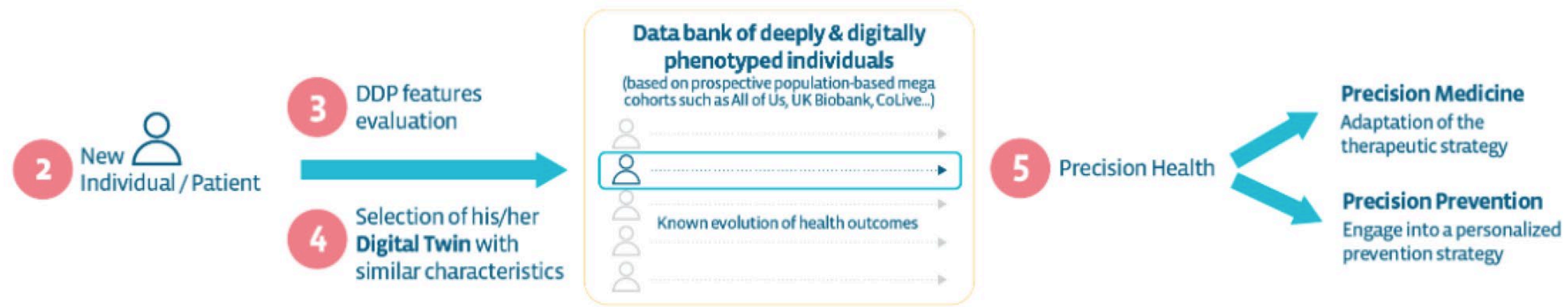
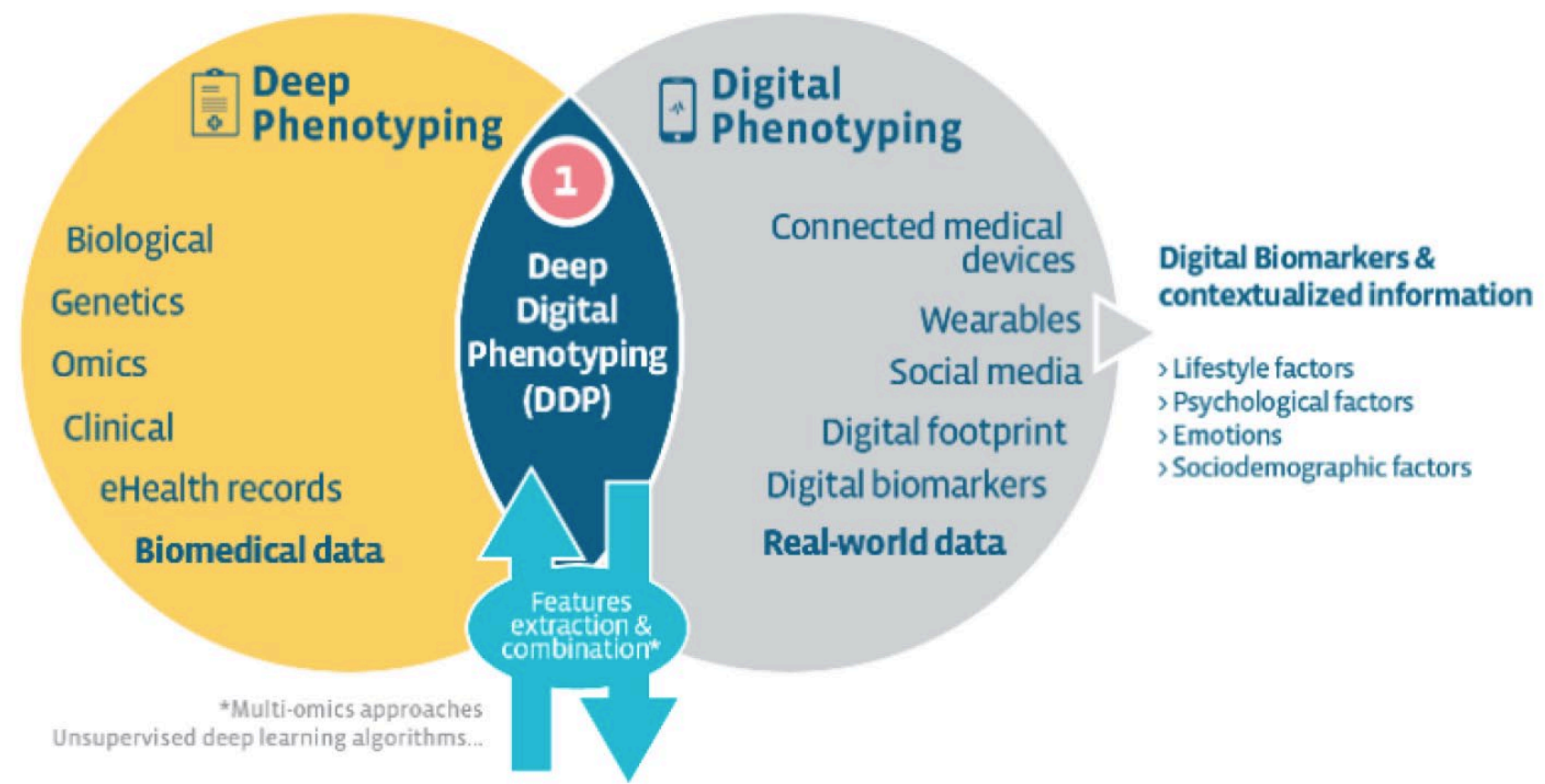
Thank you for your attention!

h.riper@vu.nl



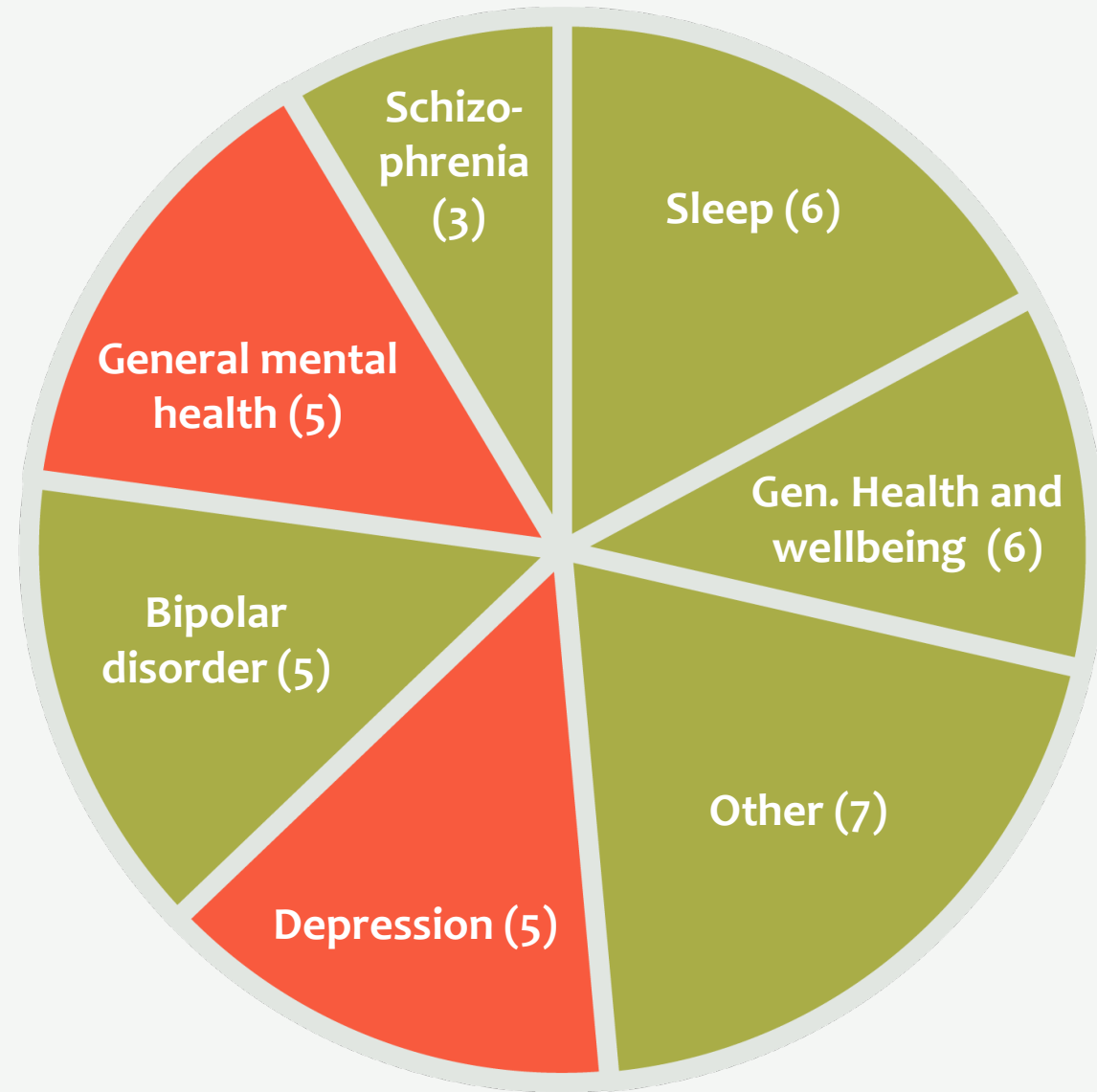


Fagherazzi (2020)
 Deep Digital
 Phenotyping and
**Digital Twins for
 Precision Health:**
 Time to Dig Deeper



Systematic review on smartphone-based passive sensing studies.

N=35 studies



Results

a.

- N =10
- pre-post design
- small sample sizes (8-48)

b.

- prediction accuracy of mood 55% - 86%

c.

- 2 replications
- 2 + JITI's
- only 1 clinical sample
- healthy students

d.

- ML methods compared
- Outcomes v GS or EMA
- AI journals ++



sentimenticsTM
remarkable text analytics



Ward van Breda, VU



ORIGINAL RESEARCH
published: 14 May 2019
doi: 10.3389/fpsyg.2019.01065

Validating Automated Sentiment Analysis of Online Cognitive Behavioral Therapy Patient Texts: An Exploratory Study

Simon Provoost^{1*}, Jeroen Ruwaard^{2,3}, Ward van Breda⁴, Heleen Riper^{1,2,3,5} and Tibor Bosse⁶

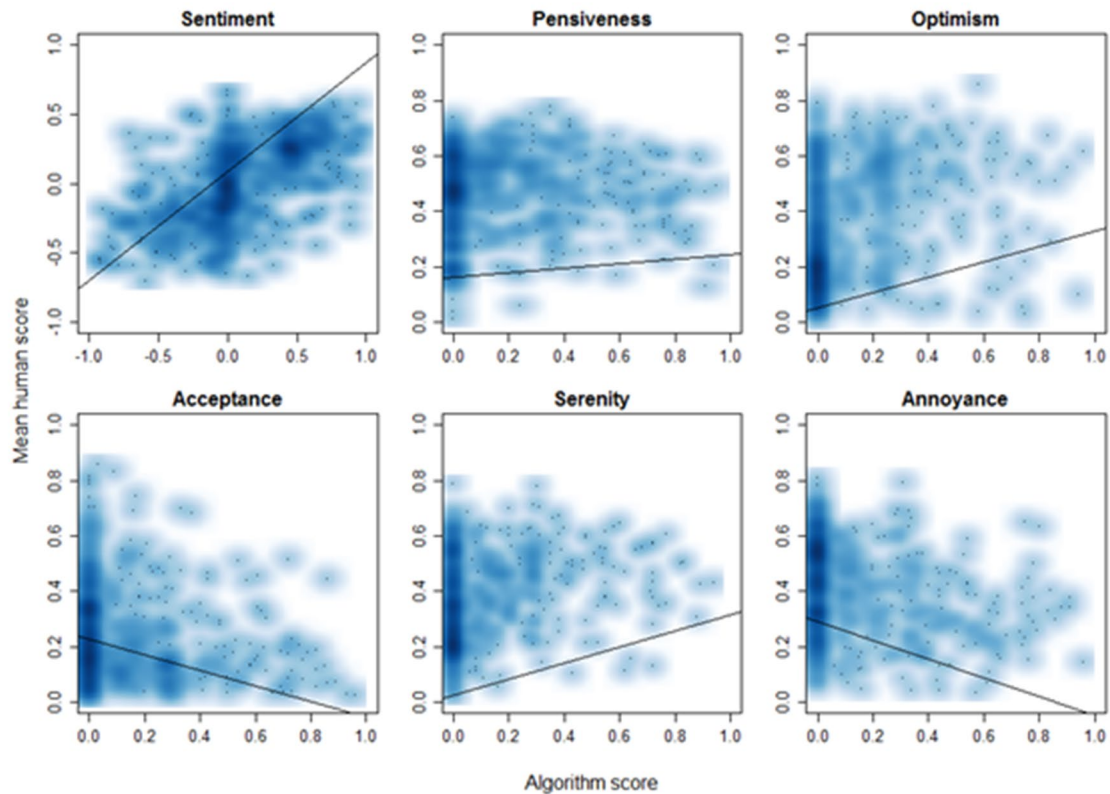
Kooistra, Wiersma, Ruwaard, Neijenhuijs, Lokkerbol, van Oppen, Smit, Riper (2019, accepted JMIR) Costs and effectiveness of blended versus standard cognitive behavioral therapy for depressed outpatients in routine specialized mental healthcare: a pilot randomized controlled trial.



Results

Intra-class correlation of algorithm versus human judgment was moderate, but only for sentiment.

The intra-class correlation among human judges, however, was not much better.



	Human – Algorithm	Human – Human
Sentiment	.55 (moderate)	.58 (moderate)
Pensiveness	.12 (low)	.22 (low)
Annoyance	.00 (low)	.28 (low)
Optimism	.23 (low)	.46 (low)
Acceptance	.00 (low)	.34 (low)
Serenity	.14 (low)	.24 (low)