Mobile Sensing & Personal Health Technology

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Curriculum

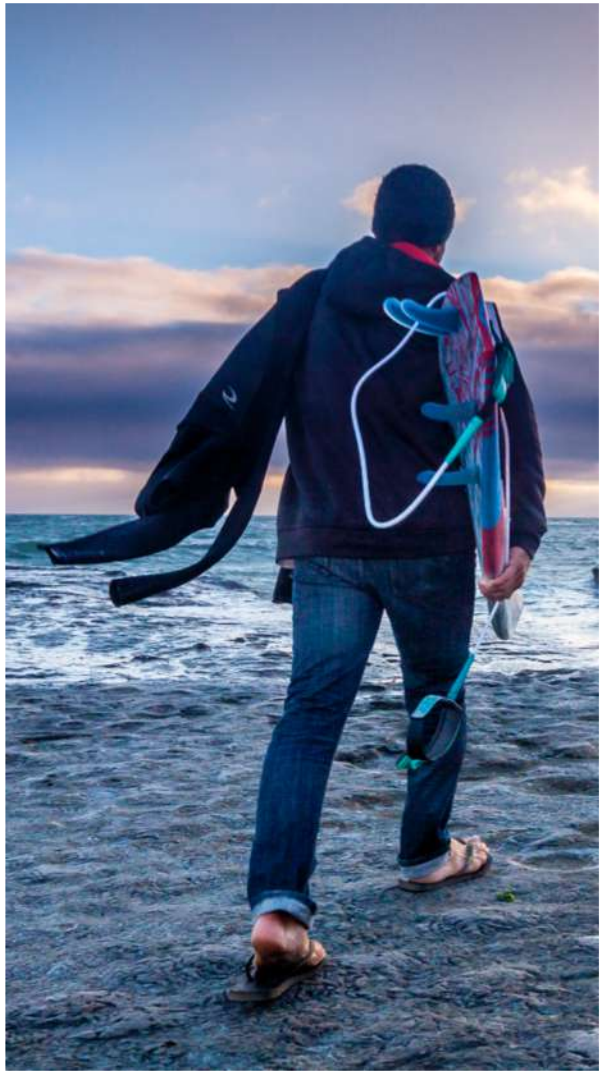
- Bardram JE, Frost M. **The Personal Health Technology Design Space**. *IEEE Pervasive Computing*. 2016;15(2):70-78.
- Lane ND, Miluzzo E, Lu H, Peebles D, Choudhury T, Campbell AT. **A survey of mobile phone sensing**. *IEEE Communication Magazine*. 2010;48(9).
- Estrin D. **Small Data, Where N = Me**. *Communication of the ACM*. 2014;57(4):32-34.
- West P, Van Kleek M, Giordano R, Weal MJ, Shadbolt N. **Common Barriers to the Use of Patient-Generated Data Across Clinical Settings**. In: *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems. CHI '18*. New York, NY, USA: ACM; 2018:484:1--484:13.
- Hollis V, Konrad A, Springer A, et al. **What Does All This Data Mean for My Future Mood? Actionable Analytics and Targeted Reflection for Emotional Well-Being**. *Human–Computer Interaction*. 2017;32(5-6):208-267.

OUTLINE OF TALK

- Mobile Sensing
- Personal Health Technology
  - architecture
  - design space
  - examples

- Cases – Mental Health
  - sensing
  - intervention

- Resources
  - frameworks
  - references



Mobile Sensing

The Smartphone

- Ubiquitous
- Unobtrusive
- Intimate
- Powerful
- Sensor-rich
- Connected – always!

- Programmable
- Easy deployment (app store)
- Cloud-enabled

”... the mobile phone has become the most ubiquitous piece of technology in our recent history” – Oliver et. al. 2015

“Smartphones offer huge potential to gather **precise**, **objective**, **sustained**, and **ecologically valid** data on the **real-world behaviors** and experiences of **millions** of people where they **already are**” – Miller, 2015

Sensing

- Sensors...
  - antennas (GSM, wifi, bluetooth, NFC, ...)
  - steps, temperature, ...
  - touch, pressure
- App logging
  - phone calls / texting
  - PIM (email, calendar, todo, ...)
  - social media
  - app usage
- External devices
  - activity trackers, scale
  - cardio (pulse, HRV, blood pressure, ECG, ...)
  - mental (breathing, sleep, EEG, ...)
  - in-ear BP/ECG
  - food

Figure 1. *An off-the-self iPhone 4, representative of the growing class of sensor-enabled phones. This phone includes eight different sensors: accelerometer, GPS, ambient light, dual microphones, proximity sensor, dual cameras, compass, and gyroscope.*

Lane ND, Miluzzo E, Lu H, Peebles D, Choudhury T, Campbell AT. A survey of mobile phone sensing. *IEEE Commun Mag*. 2010;48(9).


164.5
164.5
Withings
10:12


DietSensor


ONE DROP
ONE DROP
ONE DROP
51 mg
36g carbs

Sensing Scale

- **Personal** sensing
  - sensing by a single individual
  - produced & consumed by a sole person
  - 'single loop'
- **Group** sensing
  - sharing goal w. a group
  - sharing of sensing data (trust)
  - 'citizen science'
- **Community** sensing
  - large-scale data collection, analysis, and sharing
  - for the good of a community
  - strangers (privacy)
  - 'population sensing'

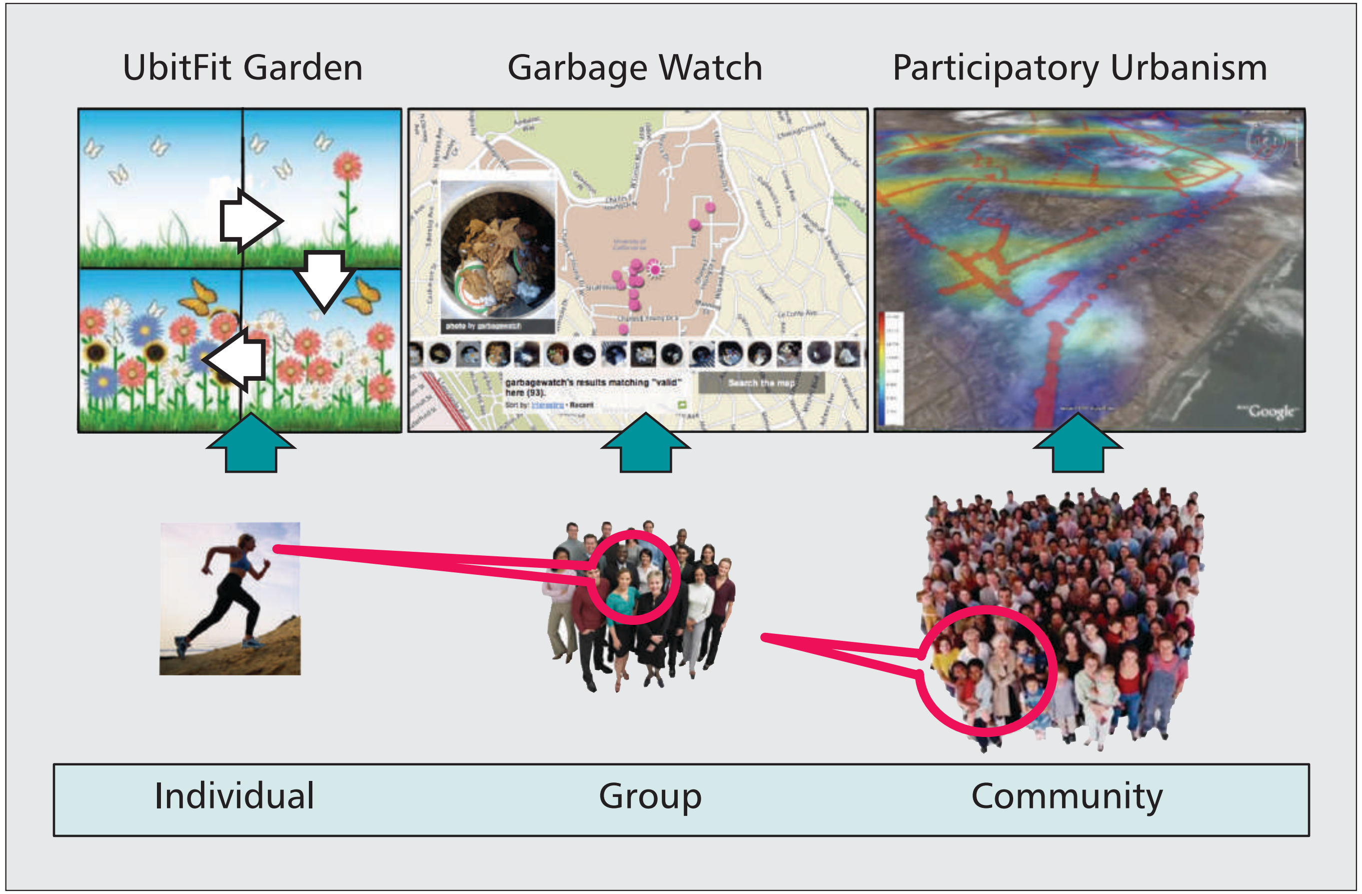


Figure 2. *Mobile phone sensing is effective across multiple scales, including: a single individual (e.g., UbitFit Garden [1]), groups such as social networks or special interest groups (e.g., Garbage Watch [23]), and entire communities/ population of a city (e.g., Participatory Urbanism [20]).*

Sensing paradigms

- Opportunistic sensing
  - data collection stage is fully automated with no user involvement
- Participatory sensing
  - the user actively engages in the data collection activity

	Opportunistic	Participatory
user’s role	none / automatic sensing	engaged in sensing
burden on user	low	high
data collection	high	low
technical complexity	high	low
data quality	low	depends on engagement
sensing context	difficult	user specific

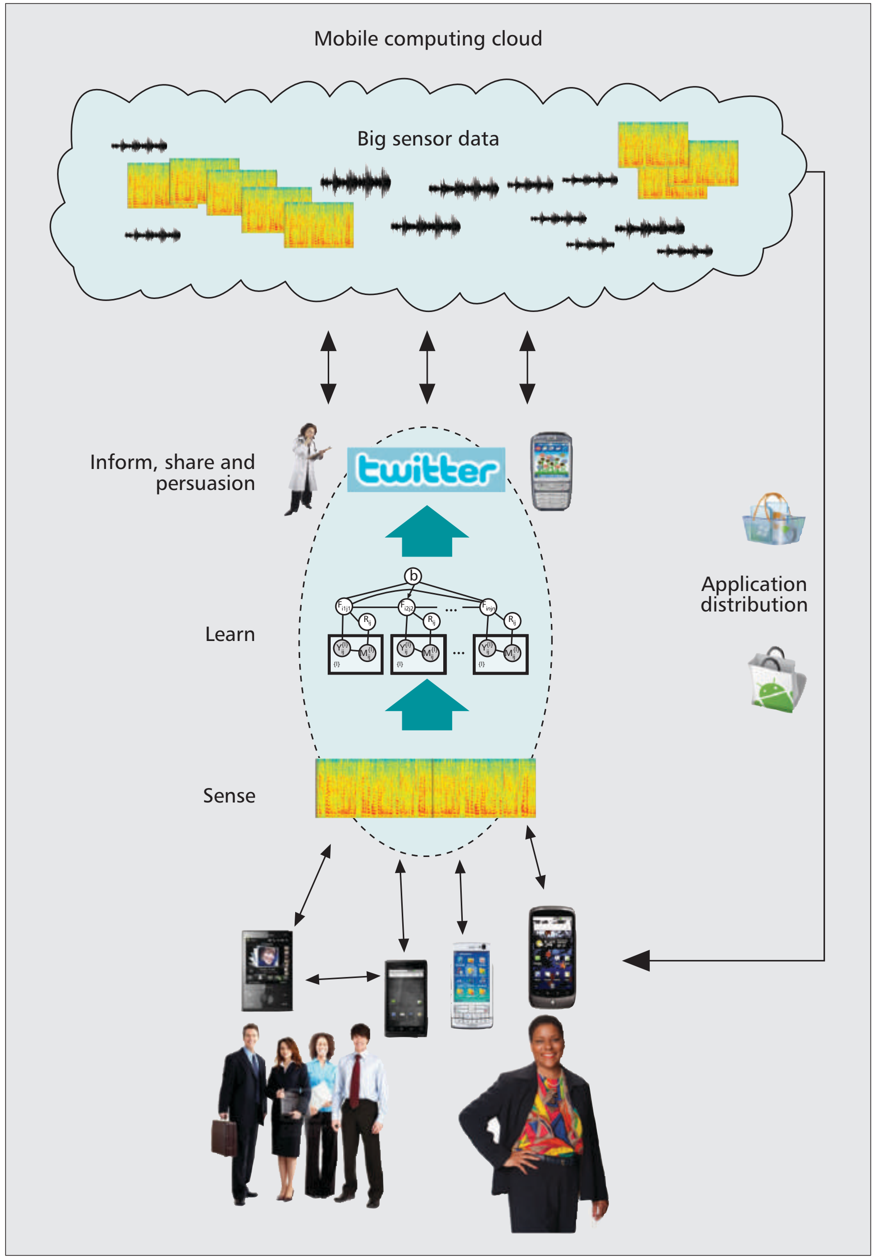


Figure 3. *Mobile phone sensing architecture.*

Mobile Sensing Architecture

- **Sense**
  - programmability – api, accessing sensors, cross-platform
  - continuous sensing – threading, resources
  - phone context – volatile, noise, unstable
- **Learn**
  - human behavior – walking, sitting, steps, ...
  - context modeling – significant places, social context, ...
- **Inform, share, and persuasion**
  - sharing – visualization (web?), SoMe, communities
  - personalized sensing – recommendations, preferences,
  - persuasion – nudge, healthy behavior, influencers, gamification
  - privacy – fundamental, trust, re-identification, "secondhand smoking"

Personal Health Technology

UbifitGarden [2008]

- obesity
- exercise
- activity recognition
- motivating feedback

Mobilyze! [2011]

- mental health
- mood assessment
- location-based coping cards

BeWell [2011]

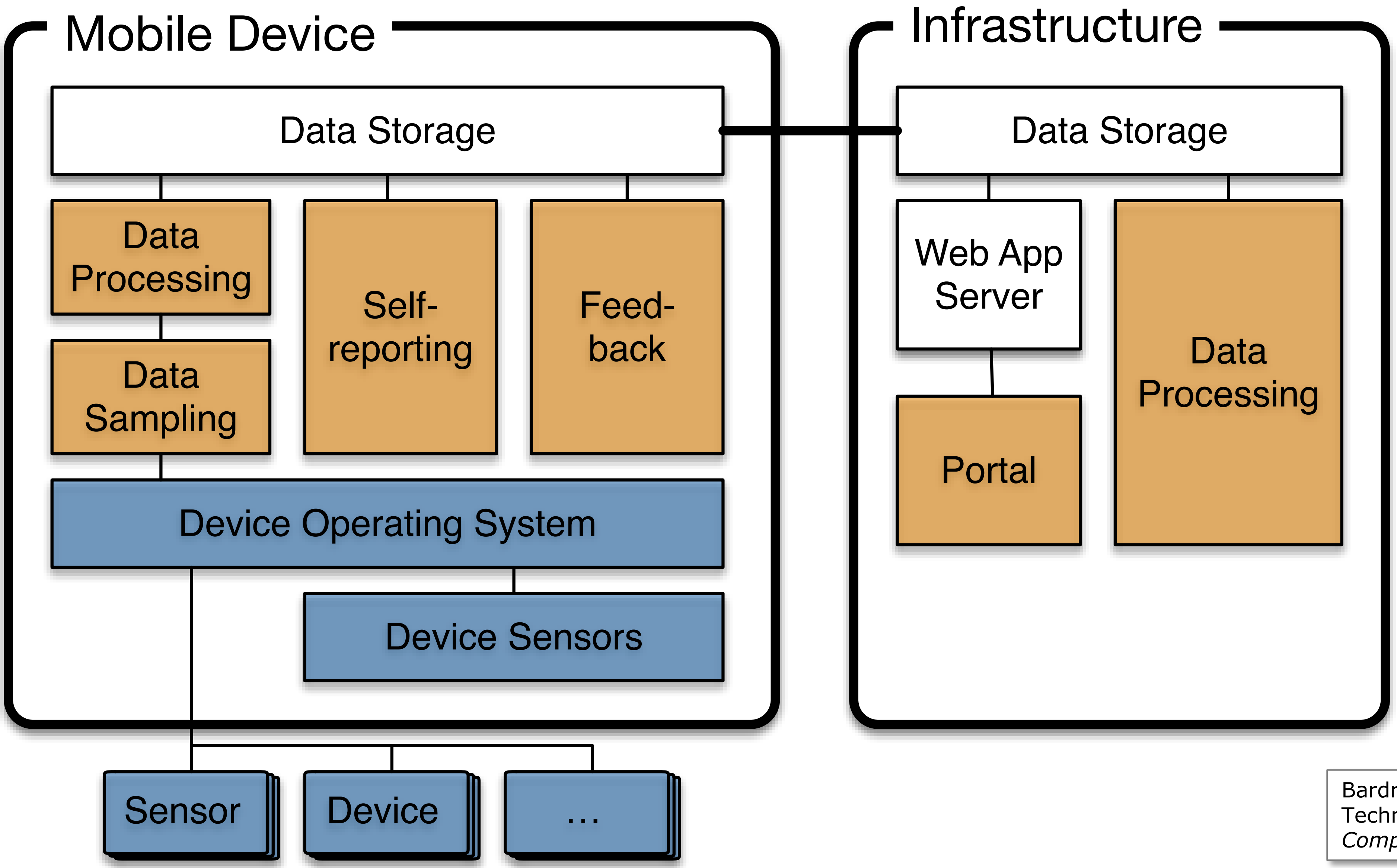
- wellness
- exercise
- social activity
- sleep

ShutEye [2012]

- sleep hygiene
- tracking sleep patterns
- food | caffeine | alcohol
- exercise | napping | relaxing

MONARCA [2013]

- mental health
- self-assessment
- tracking physical, social, mobility, and phone activity
- mood prediction
- triggers & early warning signs



Bardram JE, Frost M. The Personal Health Technology Design Space. *IEEE Pervasive Computing*. IEEE, 2016

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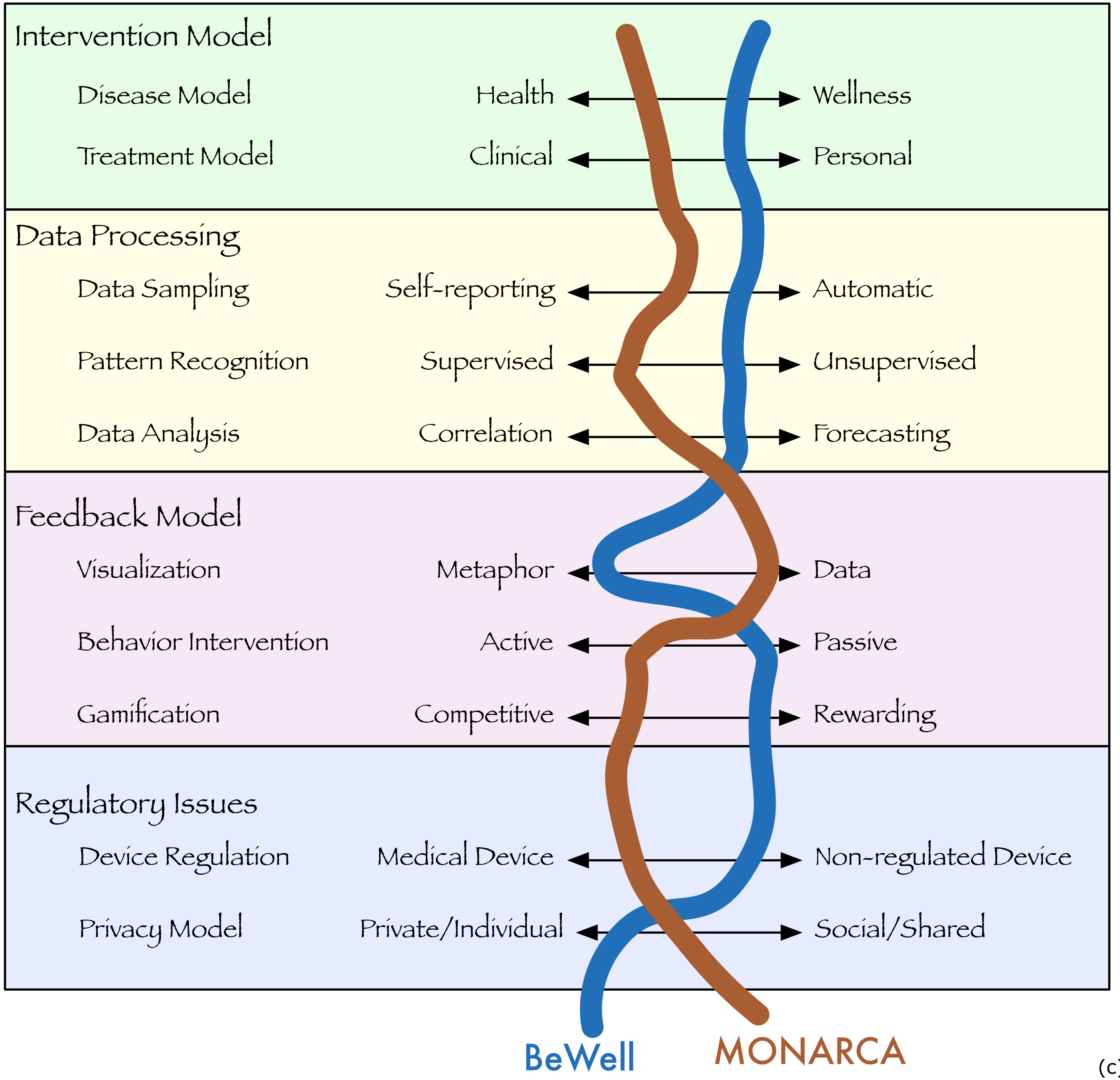

Bardram JE, Frost M. The Personal Health Technology Design Space. *IEEE Pervasive Computing*. IEEE, 2016

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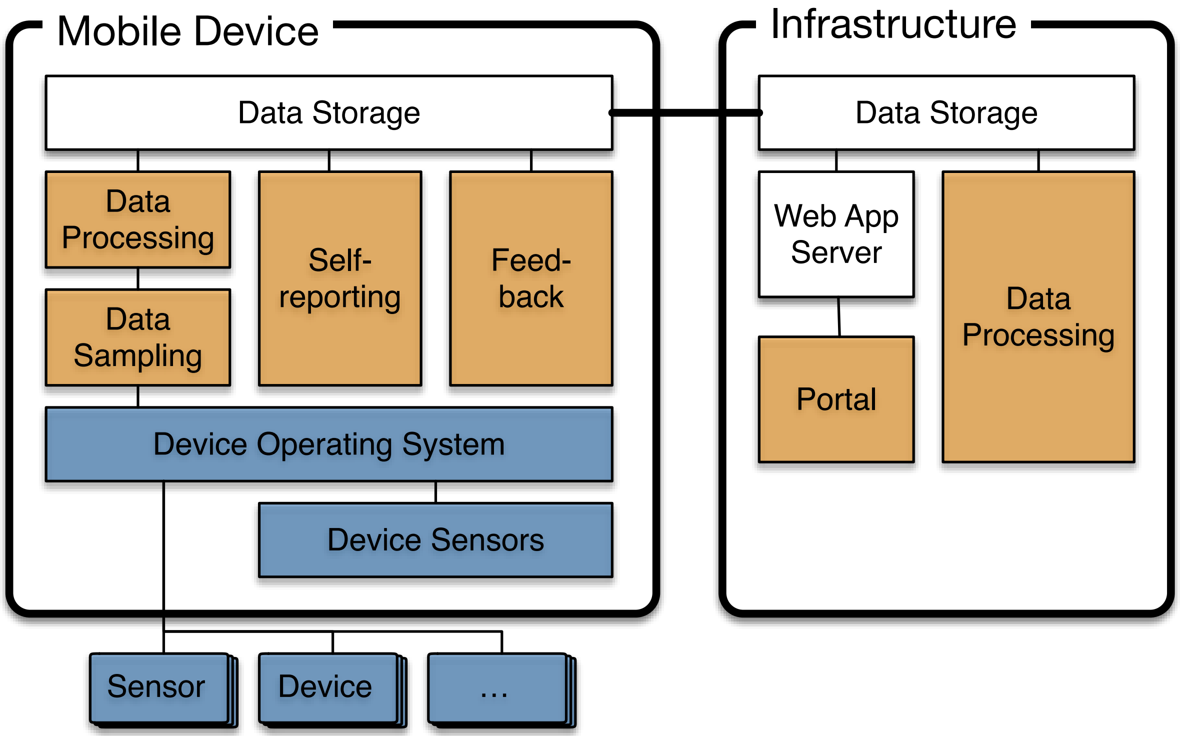
System	Focus	INTERVENTION Disease Model	INTERVENTION Treatment Model	DATA PROCESSING Data Sampling	DATA PROCESSING Pattern Recognition	DATA PROCESSING Analysis	FEEDBACK MODEL Visualization	FEEDBACK MODEL Inter-vention	FEEDBACK MODEL Gamification	REGULATORY MODEL Device Regulation	REGULATORY MODEL Privacy
BeWell	Wellness (exercise, social activity, sleep)	Wellness	Personal	Automatic	Unsupervised clasification		Metaphor (aquarium)	Passive		N/A	Individual
Mobilyze!	Depression	Health	Personal	Automatic + self-reporting	Supervised	Forecasting / Prediction	Data	Active		N/A	Individual (+Shared)
UbiFit Garden	Encourage physical activity	Wellness	Personal	Automatic + self-reporting	Unsupervised clasification		Metaphor (garden)	Passive		N/A	Individual
bant	Diabetes	Health	Personal	Automatic	Rule-based clasification		Data	Passive	Rewarding	N/A	Social/Shared
Fish'n Steps	Obesity	Wellness	Personal	Automatic (simulated)			Metaphor (fish+bowl)	Passive	Rewarding + Competing	N/A	Individual + Social
Mobile Mood Diary	Mental Health (mood charting)	Health	Clinical	Self-reporting			Data (online)	Passive		N/A	Individual
ShutEye	Sleep	Wellness	Personal	Self-reporting			Data	Passive		NA/	Individual
Mobile Health Mashups	Wellbeing & Insight	Wellness	Personal	Automatic		Correlation	Data	Passive		NA/	Individual
Monarca	Bipolar Disorder	Health	Clinical	Self-reporting + Automatic	Supervised correlation	Forecasting / Prediction	Data	Active		N/A	Shared + Individual

Personal Health Technology

- SENSING & MONITORING
  - health progression & regression
  - behavior
  - context
  - longitudinal & continuously
- LEARNING & PREDICTING
  - pattern recognition
  - correlation analysis
  - disease forecasting
  - clinical alerts & decision-support
- FEEDBACK & INTERVENTION
  - early detection
  - context-aware feedback & treatment
  - clinical intervention & prescription



CASE – MENTAL HEALTH

MONARCA

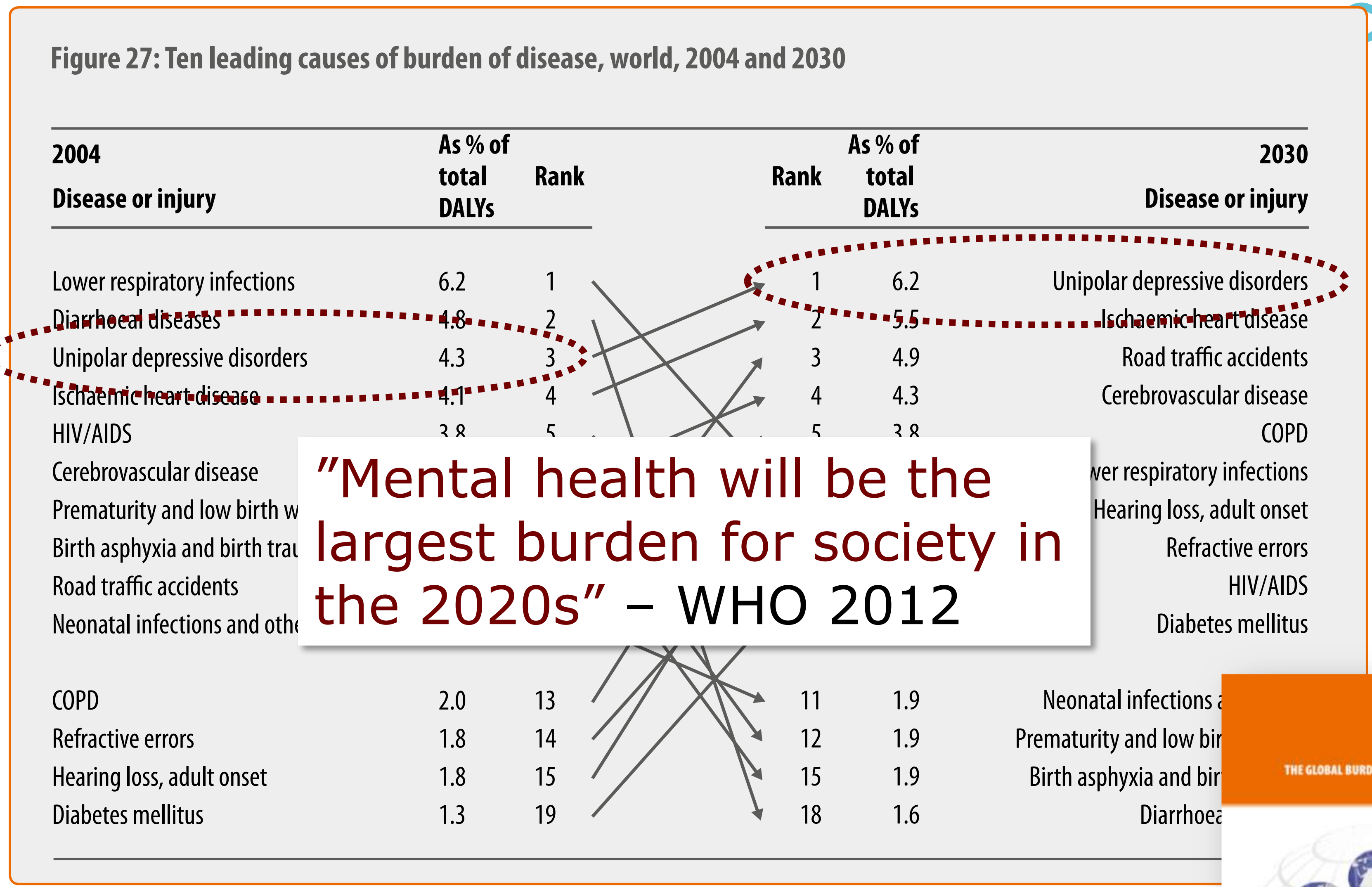
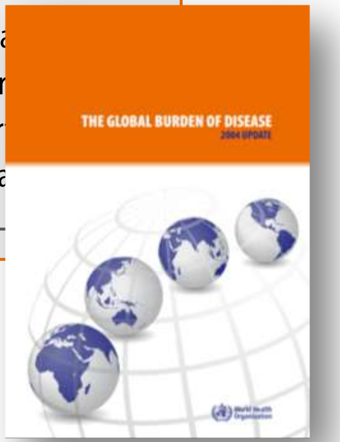


Figure 27: Ten leading causes of burden of disease, world, 2004 and 2030

2004 Disease or injury	As % of total DALYs	Rank	Rank	As % of total DALYs	2030 Disease or injury
Lower respiratory infections	6.2	1	1	6.2	Unipolar depressive disorders
Diarrhoeal diseases	4.8	2	2	5.5	Ischaemic heart disease
Unipolar depressive disorders	4.3	3	3	4.9	Road traffic accidents
Ischaemic heart disease	4.1	4	4	4.3	Cerebrovascular disease
HIV/AIDS	3.8	5	5	3.8	COPD
Cerebrovascular disease	[illegible]	[illegible]	[illegible]	[illegible]	...wer respiratory infections
Prematurity and low birth w...	[illegible]	[illegible]	[illegible]	[illegible]	Hearing loss, adult onset
Birth asphyxia and birth trau...	[illegible]	[illegible]	[illegible]	[illegible]	Refractive errors
Road traffic accidents	[illegible]	[illegible]	[illegible]	[illegible]	HIV/AIDS
Neonatal infections and othe...	[illegible]	[illegible]	[illegible]	[illegible]	Diabetes mellitus
COPD	2.0	13	11	1.9	Neonatal infections a...
Refractive errors	1.8	14	12	1.9	Prematurity and low bir...
Hearing loss, adult onset	1.8	15	15	1.9	Birth asphyxia and bir...
Diabetes mellitus	1.3	19	18	1.6	Diarrhoea...

”Mental health will be the largest burden for society in the 2020s” – WHO 2012

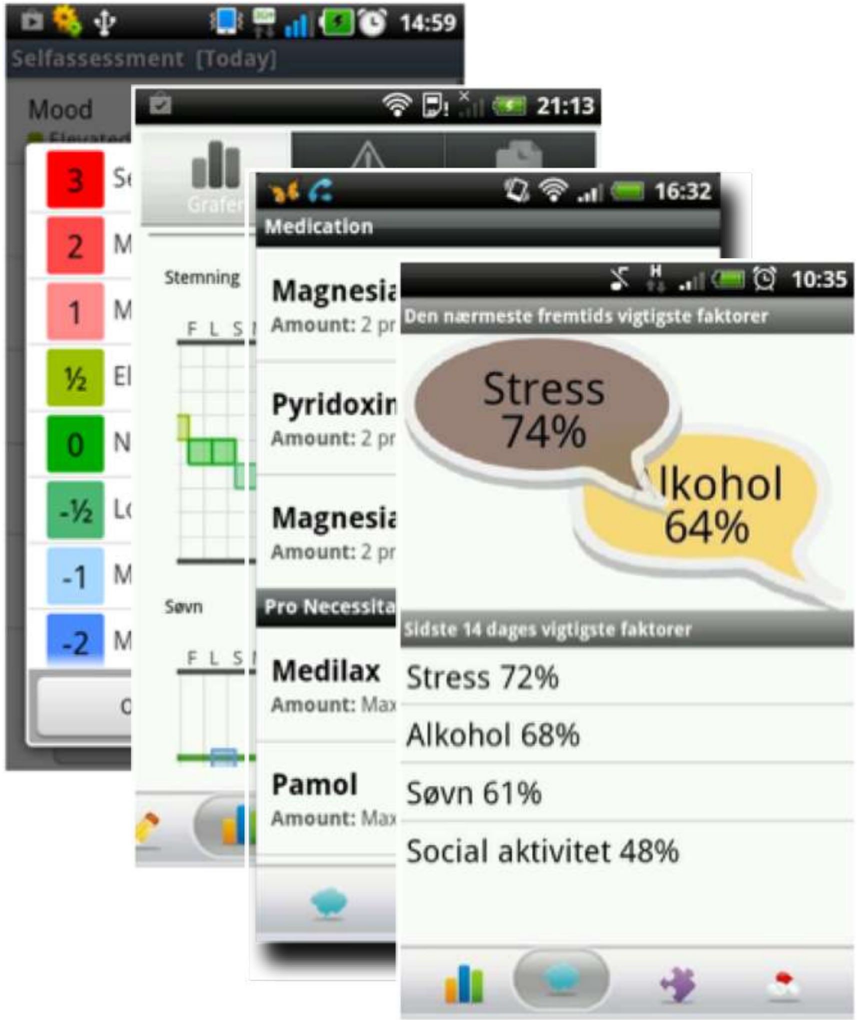


MONARCA

- Bipolar disorder (manio-depressive)
- EU STREP project w. 13 European partners.
- Copenhagen team
  - The Copenhagen Clinic for Affective Disorder, Rigshospitalet, Psychiatric Center Copenhagen,
  - The Pervasive Interaction Technology Laboratory (PIT Lab), IT University of Copenhagen, Copenhagen

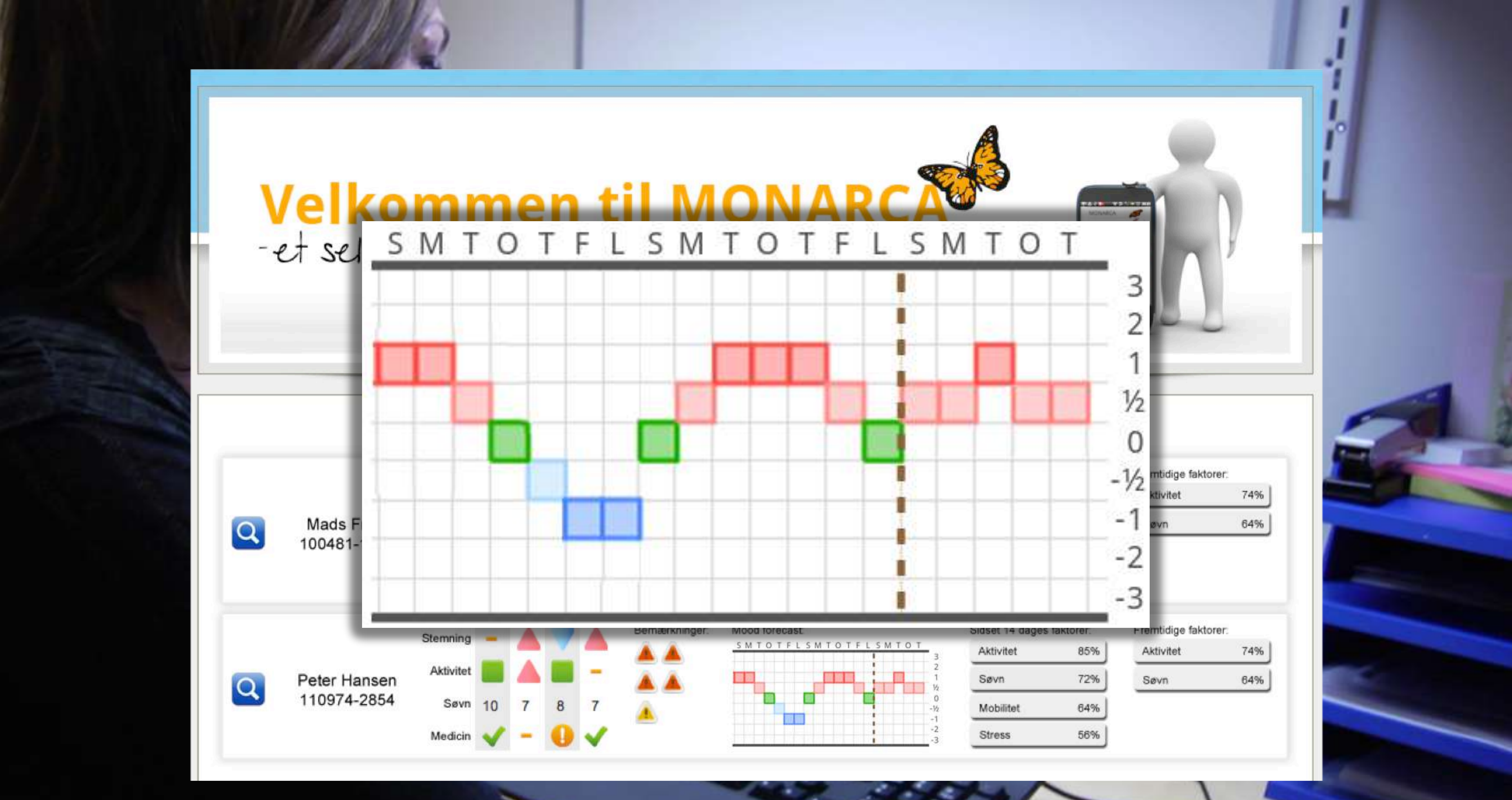
SYSTEM FEATURES

- Self-assessment (participatory sensing)
  - mood | sleep | stress | medicine | …
- Auto-assessment (opportunistic sensing)
  - 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



DOUBLE LOOP


MONARCA
Selfassessment & monitoring
Visualizations, triggers and actions-to-take
Update EWS, medicine, triggers and general actions
Patient overview and core health parameters


Velkommen til MONARCA
-et sel
S M T O T F L S M T O T F L S M T O T
3
2
1
½
0
-½
-1
-2
-3
Mads F
100481-
mtidige faktorer:
ktivitet 74%
øvn 64%
Stemning
Aktivitet
Søvn
Medicin
10 7 8 7
Bemærkninger:
Mood forecast:
Sidste 14 dages faktorer:
Fremtidige faktorer:
Peter Hansen
110974-2854
Aktivitet 85%
Søvn 72%
Mobilitet 64%
Stress 56%
Aktivitet 74%
Søvn 64%

Usefulness & Usability

Clinical evaluations have shown that the MONARCA system

- have a very high compliance rate (87-95%)
- is considered very useful and very usable by patients and clinicians
- helps patients better manage their disease
- helps clinicians in better patient treatment

CSUQ item	*Description*	*avg.*	*sd.*
OVERALL	Overall satisfaction	2.60	1.01
SYSUSE	System usefulness	1.93	0.42
INFOQUAL	Information quality	3.32	1.10
INTERQUAL	Interface quality	2.71	0.93

Table 2. The CSUQ usability results on a Likert scale from 1–7: 1=Highly agree; 7=Highly disagree.

	System Usefulness		*Perceived Usefulness*	
	avg.	*sd.*	*avg.*	*sd.*
Disease Mgmt.	3.16	1.55	2.16	1.02
Self-assessment	2.21	1.06	1.73	0.72
Visualization	2.22	1.39	1.66	0.78
Alarms	2.34	1.44	2.13	1.88
Triggers	3.59	1.31	2.71	1.02
Early Warning Signs	3.44	1.18	2.36	0.78
Actions to take	3.25	1.52	2.34	0.88
Medication	4.30	1.50	3.17	1.51
Website	3.00	1.70	2.63	1.76

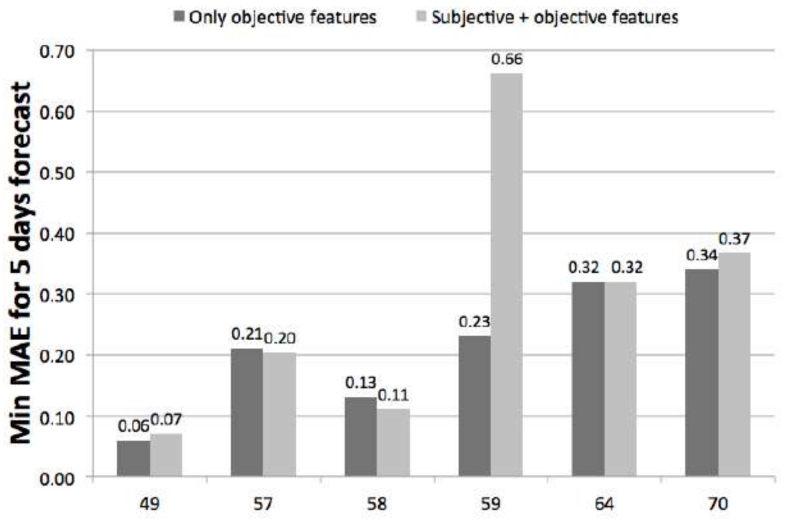
Table 3. Questionnaire results on 'System Usefulness' as used in the trial period and 'Perceived Usefulness' in the future. Users reported on a 1–7 point Liket scale on the question of "The MONARCA system is useful for ...": 1=Highly agree; 7=Highly disagree.

JE Bardram et al. 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*, p. 2627-2636, ACM, 2013.

Mood Forecasting

- Mood Forecasting
  - mean-absolute-error (MAE) is between 0.06 and 0.66 (±3 scale)
  - in 4 out of 6 cases, MAE is lower w. only objective data
  - i.e. mood forecasting can be done using only <u>objective data</u>

- Impact Factors – Top 5
  - Activity | Stress | Sleep
  - Phone Usage* | Social Activity*



Data features	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Activity	3	1	1	1	0	0	0	0	0	0	0	0	0	0
Stress	1	1	2	0	1	0	1	0	0	0	0	0	0	0
Sleep	0	1	0	3	2	0	0	0	0	0	0	0	0	0
Phone Usage*	1	0	3	0	0	0	1	0	0	0	0	1	0	0
Social Activity*	0	2	0	1	0	0	1	0	1	0	1	0	0	0
Irritability	0	0	0	0	2	2	0	1	1	0	0	0	0	0
Cognitive Problems	0	1	0	1	0	1	1	0	1	0	0	0	1	0
Physical Activity*	1	0	0	1	0	0	1	0	1	1	0	1	0	0
Alcohol	0	0	0	1	0	1	1	2	0	0	0	0	1	0
Warning Signs	0	0	0	0	1	1	0	1	1	1	0	0	1	0
Mobility*	0	0	0	0	0	1	0	2	0	1	1	1	0	0
Mixed Mood	0	0	0	0	0	0	1	1	1	0	0	0	0	3
Medicine Changed	0	0	0	0	0	0	0	1	0	0	2	1	1	1
Medicine Taken	0	0	0	0	0	0	0	0	0	0	0	2	2	2

Table 2. Ranking of the correlation between Impact Factors (features) and the mood score. The objective features are marked with *.

M Frost et al. Supporting disease insight through data analysis. in *Proceedings of the 2013 ACM international joint conference on Pervasive and Ubiquitous computing*, ACM, 2013.

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Clinical Correlations

- Clinical Study
  - N=61 | 6 m | 19 m
  - HDRS-17 (depression) and YMRS (manic)
  - 400+ clinical ratings (monthly)
- Results
  - significant correlations between self-rated mood and HDRS & YMRS
  - significant correlations between social activity and clinical ratings on both HDRS & YMRS
    - especially when grouping 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."

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

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
Activity (scale: −3 to +3)						
HDRS-17	−0.037	−0.053 to −0.020	<0.001	−0.042	−0.059 to −0.025	<0.001
YMRS	0.047	0.022–0.072	<0.001	0.048	0.023–0.072	<0.001
Stress (scale: 0 to +5)						
HDRS-17	0.047	0.029–0.065	<0.001	0.046	0.027–0.064	<0.001
YMRS	0.012	−0.013 to 0.033	0.34	0.012	−0.013 to 0.037	0.35

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]Total N = 30.
[c]Adjusted for age 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.

Voice Feature Analysis

- Collection of voice features in naturalistic setting
  - N=28 | 12 w
  - HDRS-17 (depression) and YMRS (manic)
  - 179 clinical ratings (fortnightly)
  - openSMILE (emolarge)
- Classification results (user-specific models), accuracy (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."

Table 3. Classification of affective states based on voice features

	Accuracy (s.d.)[a]	*Sensitivity (s.d.)*[b]	*Specificity (s.d.)*[c]
User-dependent models[d]			
A depressive state[e] versus a euthymic state[f] ($n = 13$)	0.70 (0.13)	0.64 (0.25)	0.75 (0.23)
A manic or mixed state[g] versus a euthymic state[f] ($n = 3$)	0.61 (0.04)	0.71 (0.09)	0.50 (0.08)
User-independent models[d]			
A depressive state[e] versus a euthymic state[f]	0.68 (0.006)	0.81 (0.008)	0.56 (0.008)
A manic or mixed state[g] versus a euthymic state[f]	0.74 (0.005)	0.97 (0.002)	0.52 (0.01)

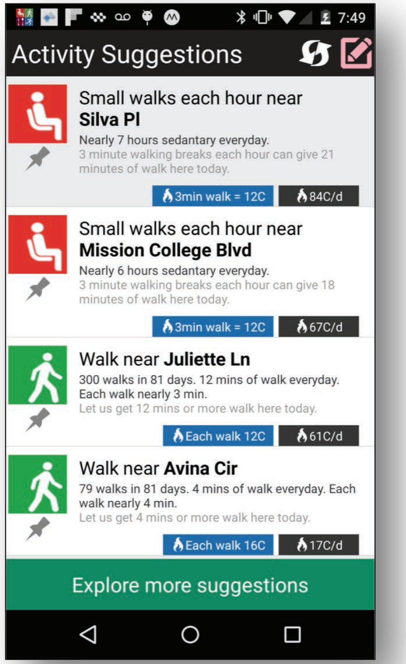
Abbreviations: HAMD, Hamilton Depression Rating Scale 17-item; YMRS, Young Mania Rating Scale. Data are mean and s.d. [a]Defined as accuracy = (true positive+true negative)/ (positive+negative). [b]Defined as sensitivity = true positive/positive. [c]Defined as specificity = true negative/negative. [d]User-dependent models: building a model from each individual patient. User-independent models: building a common model from all patients. [e]Defined as a HAMD score ⩾ 13 and a YMRS score < 13. [f]Defined as HAMD < 13 and YMRS < 13. [g]Defined as a YMRS score ⩾ 13.

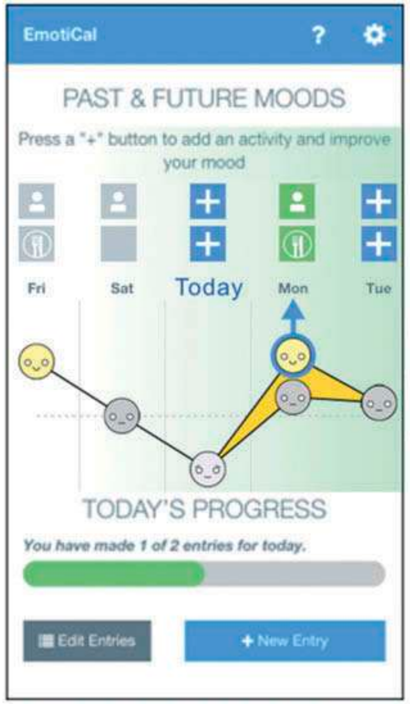
M Faurholt-Jepsen, J Busk, M Frost, M Vinberg, EM Christensen, O Winther, JE Bardram and LV Kessing. Voice analysis as an objective state marker in bipolar disorder. *Transl Psychiatry* (2016) 6

OPPORTUNITIES FOR INTERVENTION

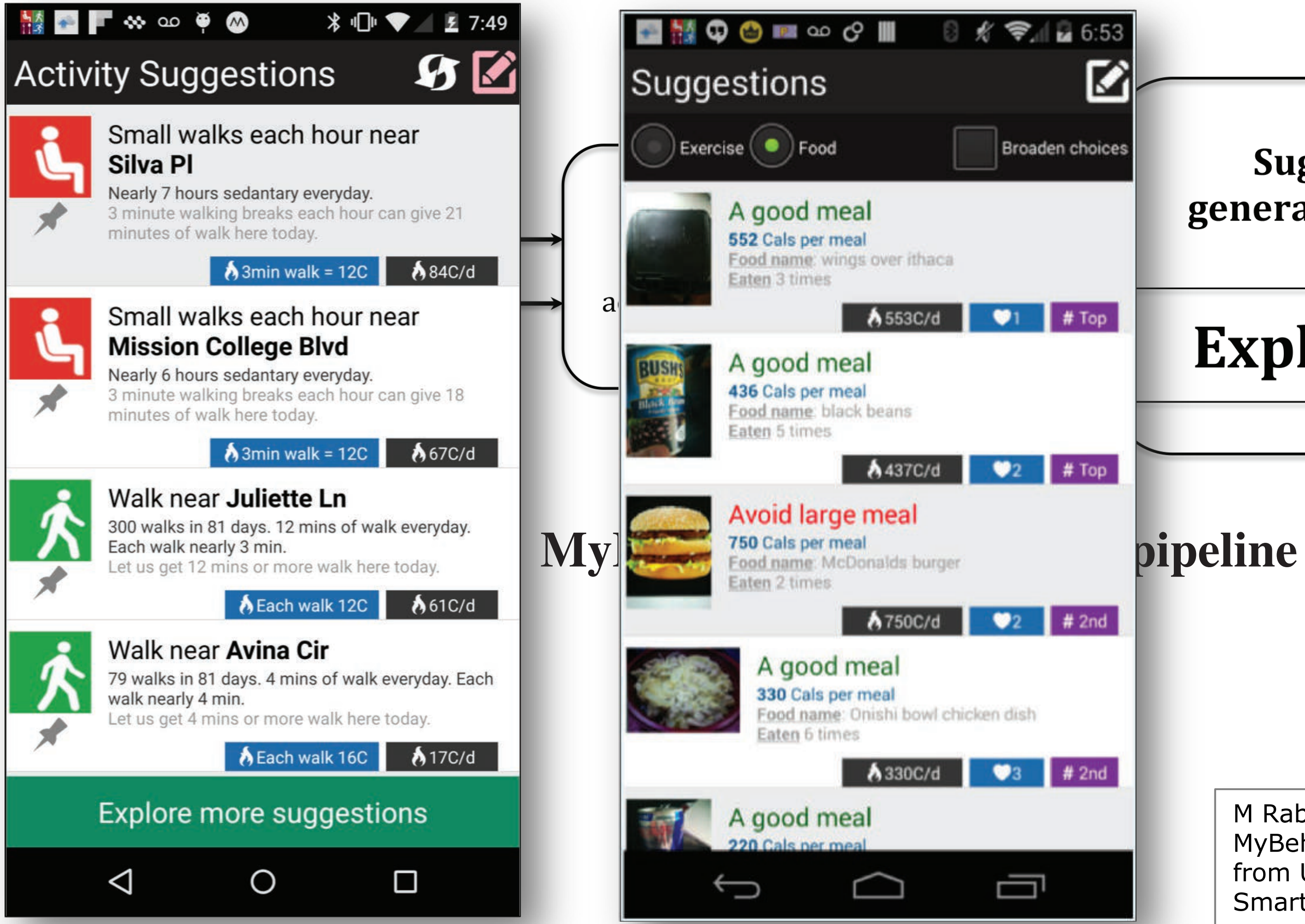
From Monitoring to Intervention

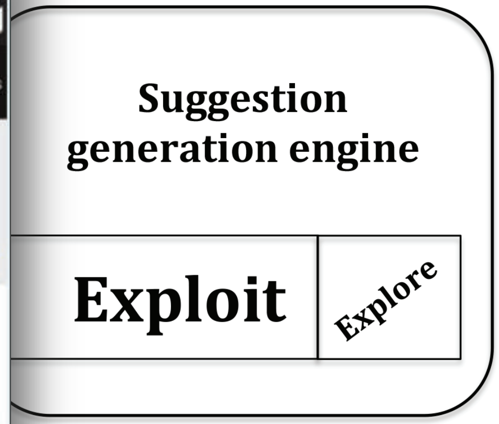
- MyBehavior
  - Cornell University, USA
- MOOS – Mobile Sensing and Support
  - University of St Gallen, Switzerland
- EmotiCal – Emotional Calendar
  - University of California at Santa Cruz, USA





MyBehavior





M Rabbi, MH Aung, M Zhang, T Choudhury. MyBehavior: Automatic Personalized Health Feedback from User Behaviors and Preferences using Smartphones. In *Proc. of Ubicomp 2015*. ACM.

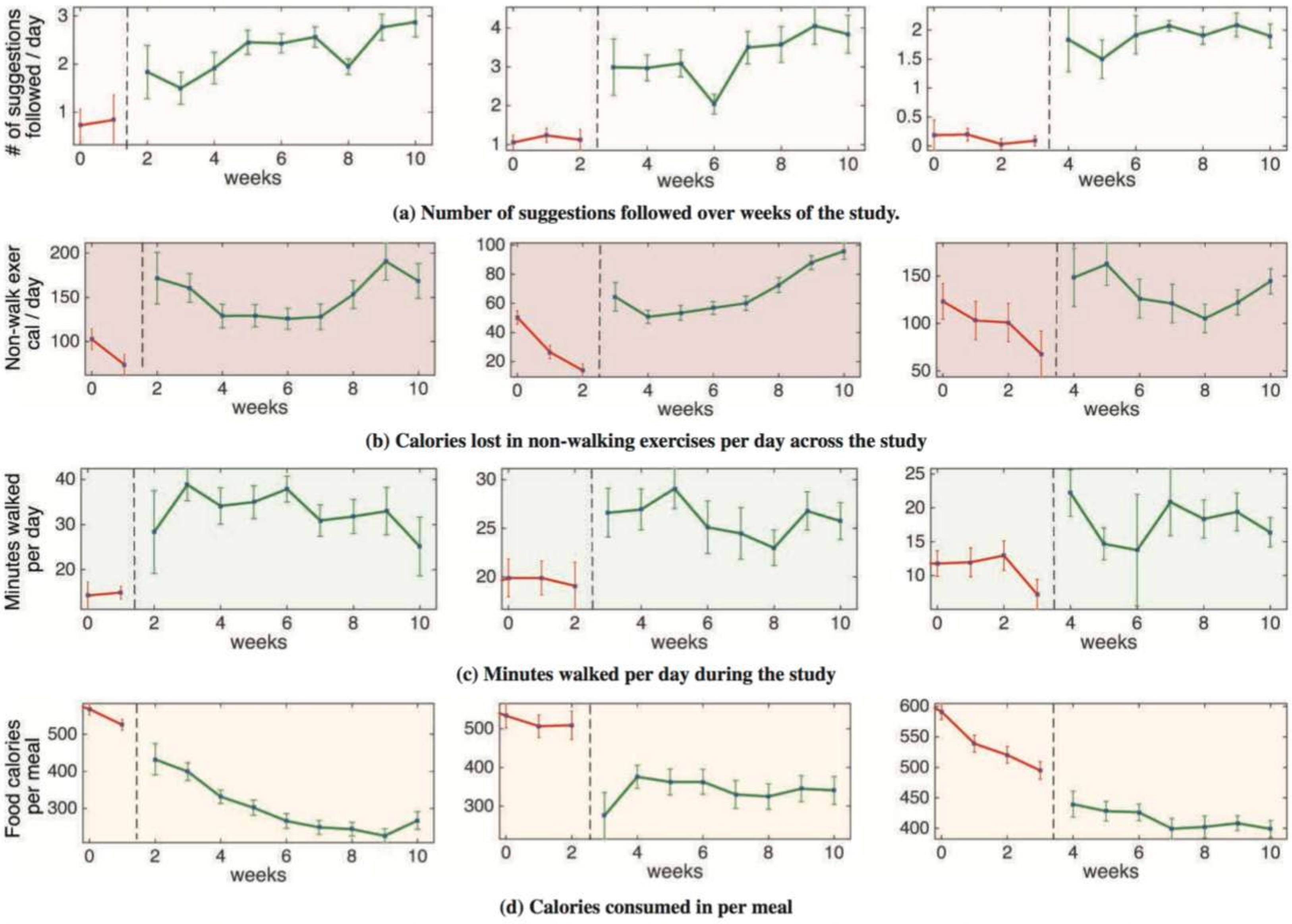


Figure 6: Changes in user behavior as predicted by the mixed model for multiple baseline design. The dotted lines represent the start of the intervention of MyBehavior. Left, middle, and right figures respectively show results from participants where intervention were started after 2, 3 and 4 weeks of using the control. Red color represents control phase where as green represents periods of using MyBehavior.

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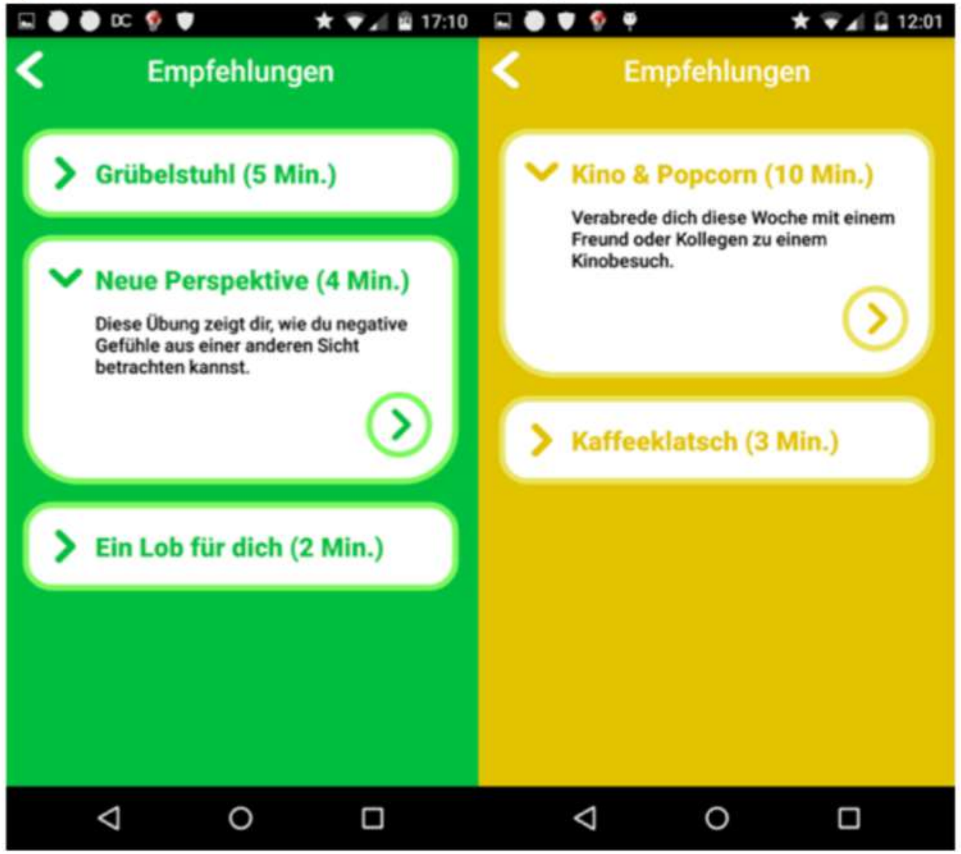
MOOS

Figure 4. Sample screenshots of lists of interventions of two different baskets. Each item shows the approximate time it takes to carry out the intervention together with a short summary (in German language) Note: The left, green list presents 3 mindfulness exercises: “muse chair,” “new perspective,” and “praise yourself.” The right, yellow list presents 2 social exercises: “Movies&Popcorn” and “kaffeeklatsch.”.



Wahle F, Kowatsch T, Fleisch E, Rufer M, Weidt S. Mobile Sensing and Support for People With Depression: A Pilot Trial in the Wild. *JMIR mHealth uHealth*. JMIR Publications Inc.; 2016;4(3).

MOOS Study

- Study setup
  - Single arm, pilot study
  - N=126
  - 4 weeks
  - PHQ-9 > 10 (clinically relevant)

- Results
  - N=12
  - for participants PHQ-9 > 10 + app adherence, a significant drop in PHQ-9 was observed.
  - able to distinguish between subjects above and below PHQ-9 = 10

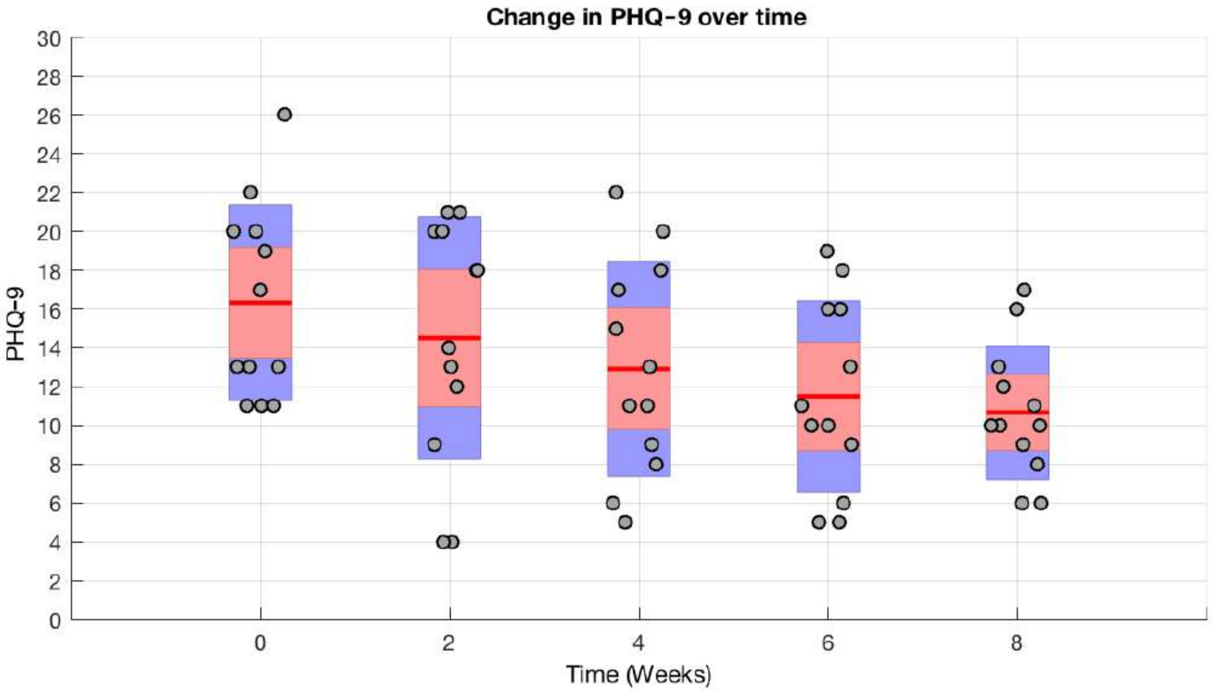
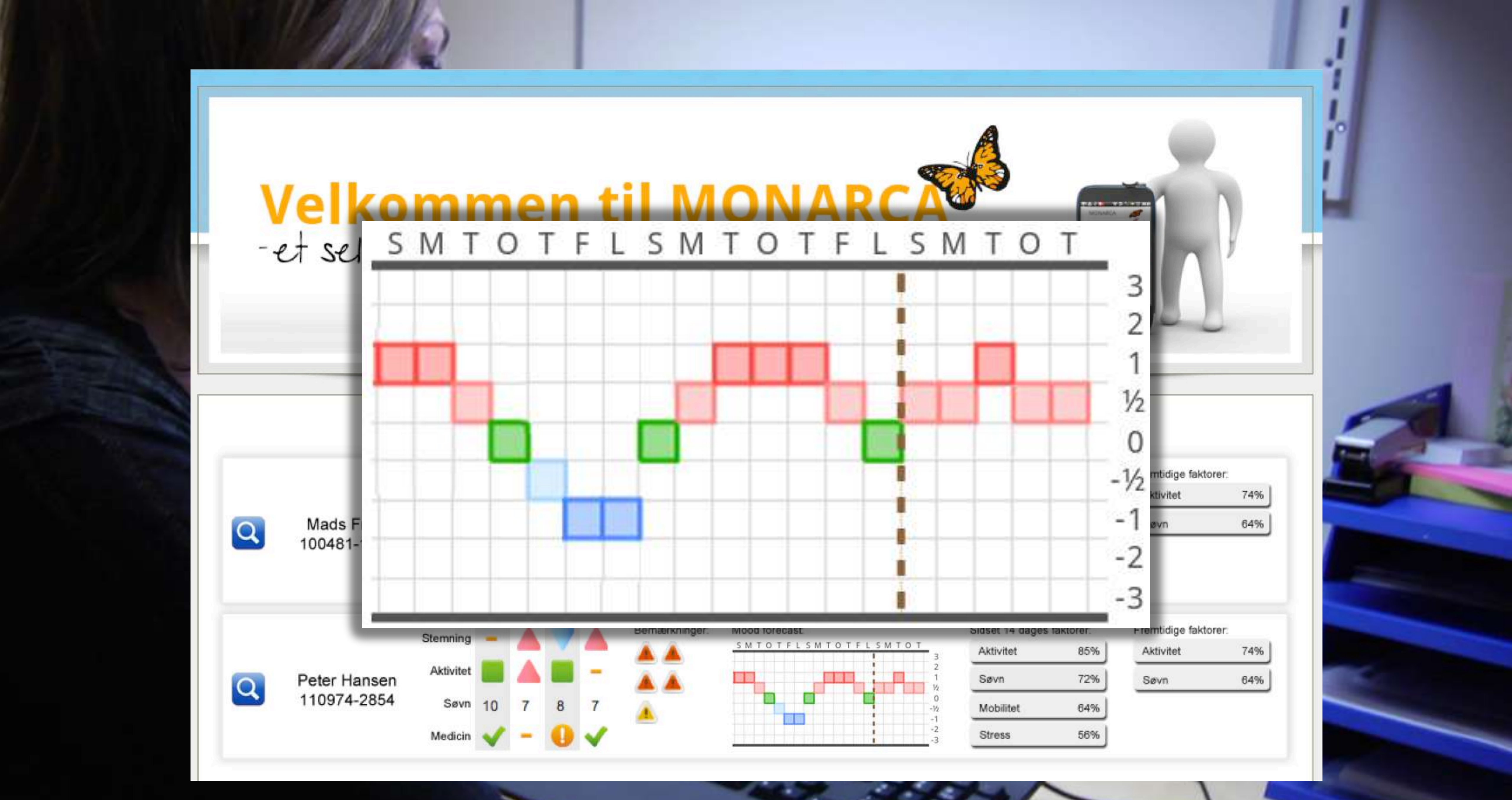


Table 4. Classification performance of support vector machines and random forest classifier.

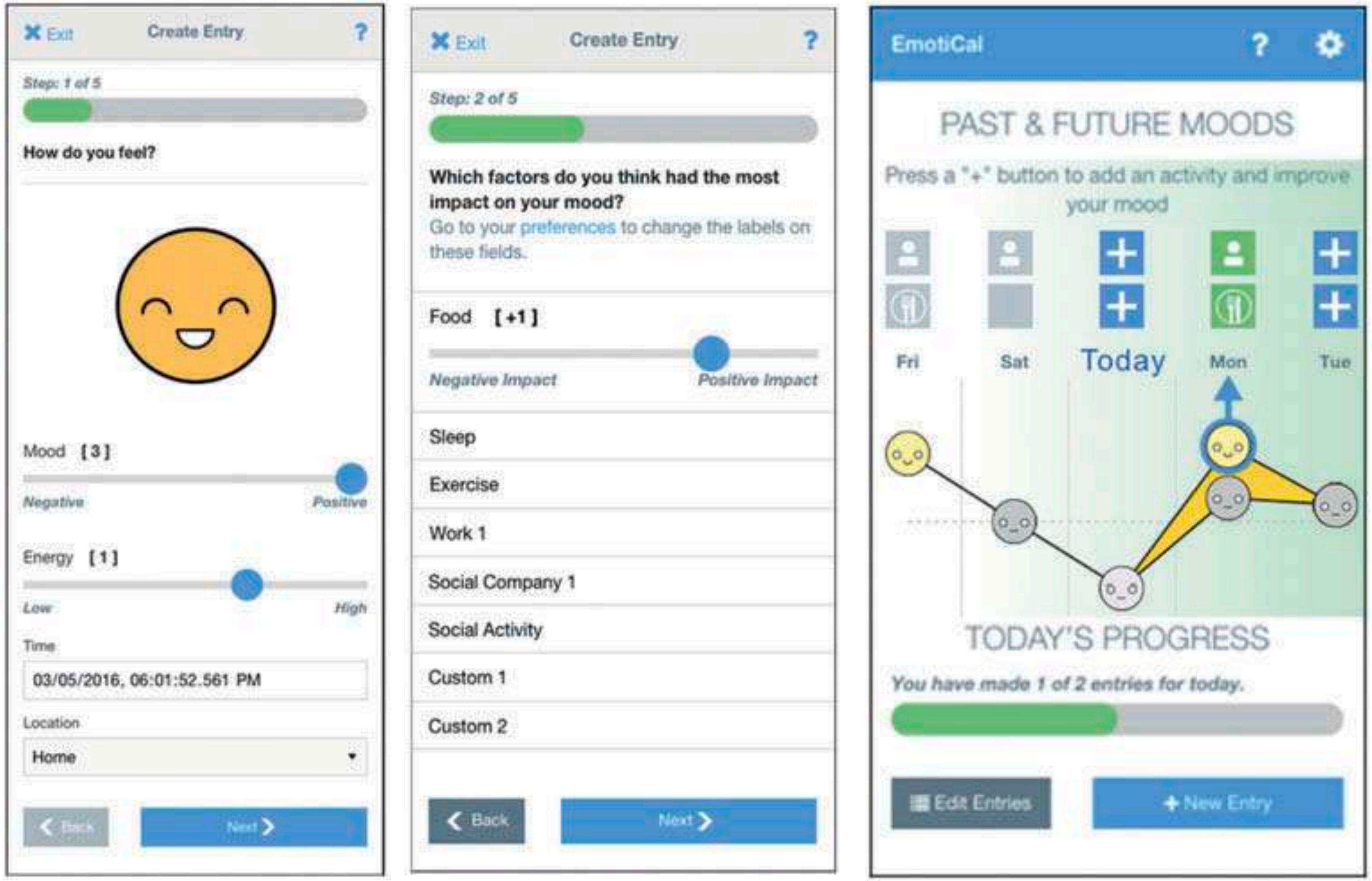
PHQ-9[a]≥11 vs PHQ-9≤10 classification performance	Support vector machines, radial basis function kernel	Random forest classifier, ntrees = 450
Accuracy	59.4	61.5
Sensitivity	72.5	62.3
Specificity	47.3	60.8



Velkommen til MONARCA
S M T O T F L S M T O T F L S M T O T
3
2
1
½
0
-½
-1
-2
-3
Peter Hansen
110974-2854
Stemning
Aktivitet
Søvn
Medicin
10 7 8 7
Bemærkninger:
Mood forecast:
Fremtidige faktorer:
Aktivitet 85%
Søvn 72%
Mobilitet 64%
Stress 56%
Aktivitet 74%
Søvn 64%

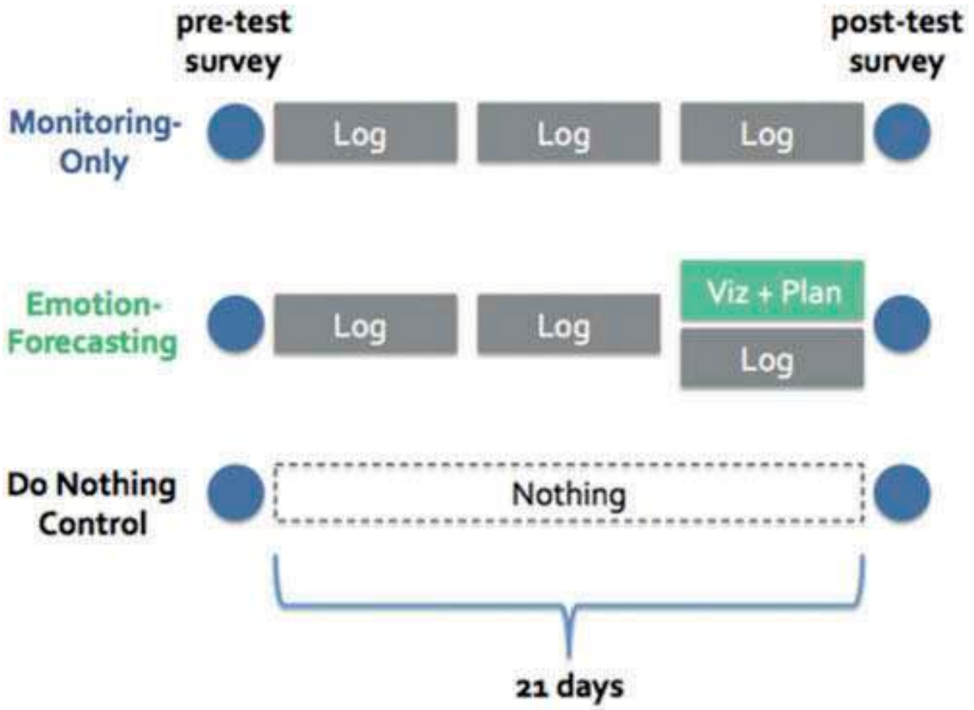
EmotiCal

- Mood Monitoring
  - 2 / day
  - mood, energy, time, location
  - trigger activities
- Emotion forecasting
  - actionable recommendations
  - motivate engagement in future activities that directly improve mood
- Recommendations for activities
  - history (5)
  - psychological needs (5)



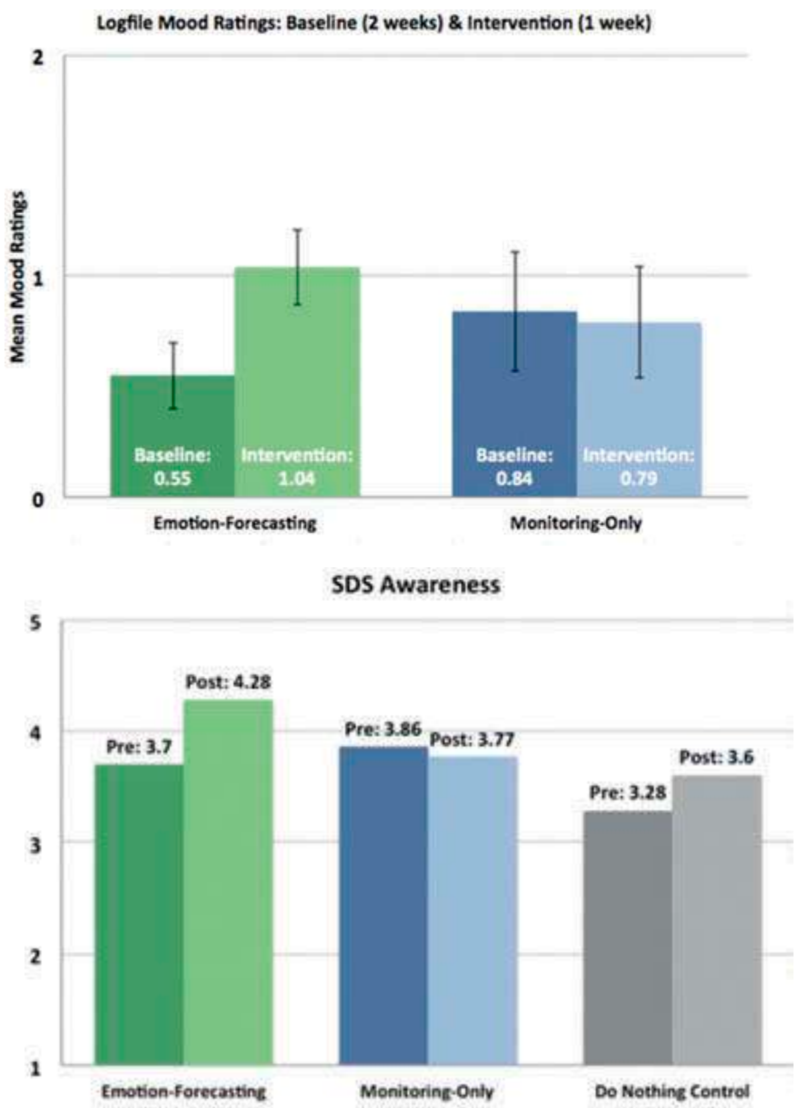
EmotiCal Study

- 3 week
- N = 36/60 | random, not ill
- $10
- 3 arms
  - monitoring only
  - emotion forecasting
  - control
- Surveys
  - Positive and Negative Affect Scale [PANAS]
  - Psychological needs (BPNS)
  - Self-awareness, and perceived choice over behavior (Self-Determination Scale [SDS])
  - Pleasant Activities Schedule



EmotiCal Study Results

- Emotion-forecasting participants had more positive mood records with greater use of cognitive mechanism and insight terms
- Emotion-forecasting participants had higher ratings of self-awareness,
  - but no differences in perceived choice or PANAS Scores
- ... and some more



RESOURCES – FRAMEWORKS & REFERENCES

TRY YOURSELF! (FRAMEWORKS)

- Goggle Sensor & geolocation API [Google]
- Goggle Activity Recognition API [Google]
- Sensus [University of Virginia]
- Funf [MIT/Google]
- AWARE [University of Oulu Center for Ubiquitous Computing]
- PACO [Google]
- EmotionSense [University of Cambridge]
- Purple Robot [Center for Behavioral Intervention Technologies, Northwestern University]
- ResearchKit / CareKit [Apple]
- ResearchStack [Cornell]
- Open mHealth [Open mHealth]

- See
  - https://en.wikipedia.org/wiki/Mobile_phone_based_sensing_software

Google APIs for Android

PACO
The Personal Analytics Companion

EMOTIONSENSE

predictive-technology-laboratory / sensus

AWARE
Android Mobile Context Instrumentation Framework

Open mHealth

ResearchKit

CareKit

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