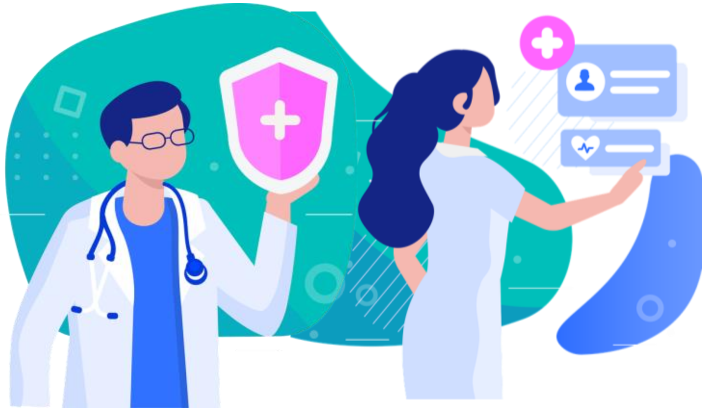

Smart Sensing in Mental Health

Digital Technology: Novel possibilities in Early Recognition of Mental Illness and Interventions

Yannik Terhorst
Department of Clinical Psychology and Psychotherapy
Ulm University
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@YannikTerhorst

Smart Sensing

Ambulatory Assessment

Affective Computing

Mobile Logging

Real-time Assessment

Health recognition

Ubiquitous Sensing

Smart Sensing

Digital Biomarkers

Passive Sensing

Experience Sampling

Digital Phenotyping

Crowdsensing

Ecological Momentary Assessment

Mobile Sensing

Smart Sensing: A Working-Definition

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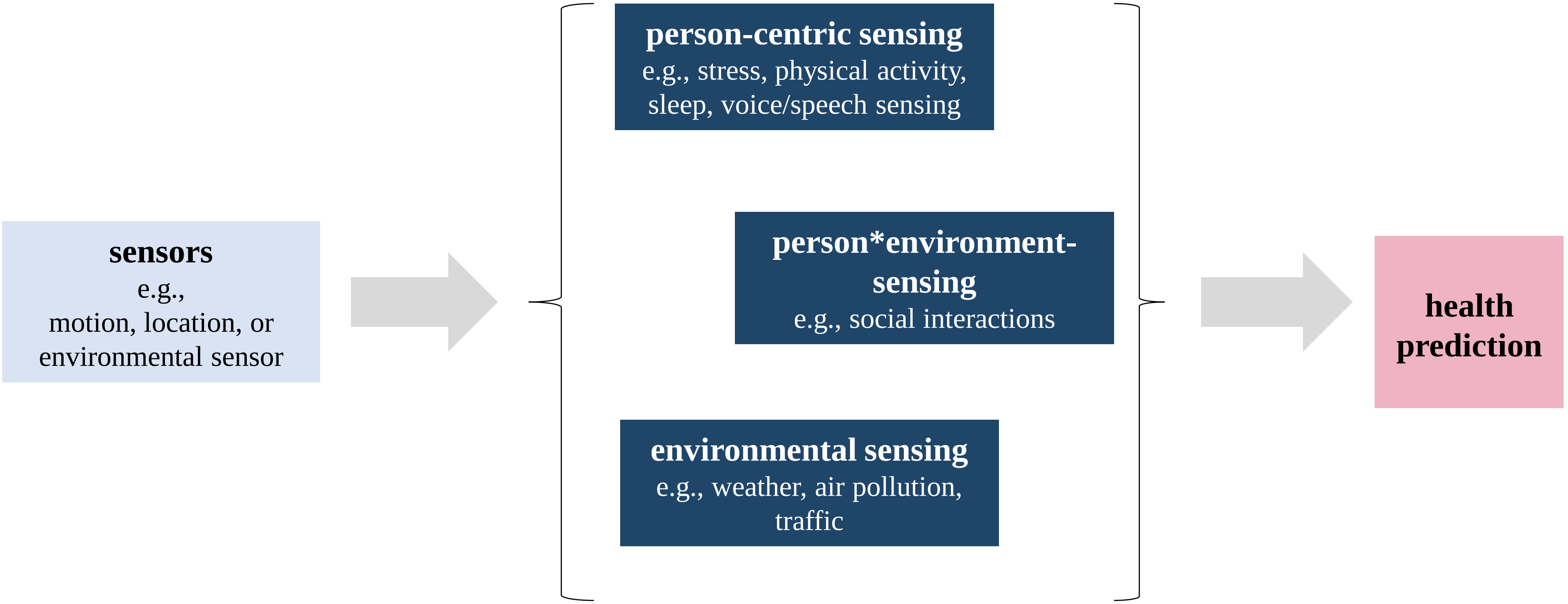
Smart Sensing



Garatva, P., Terhorst, Y., Messner, E.-M., Karlen, W., Pryss, R., Baumeister, H., 2022. Smart Sensors for Health Research and Improvement, in: Montag, C., Baumeister, H. (Eds.), Digital Phenotyping and Mobile Sensing. Springer, Berlin.

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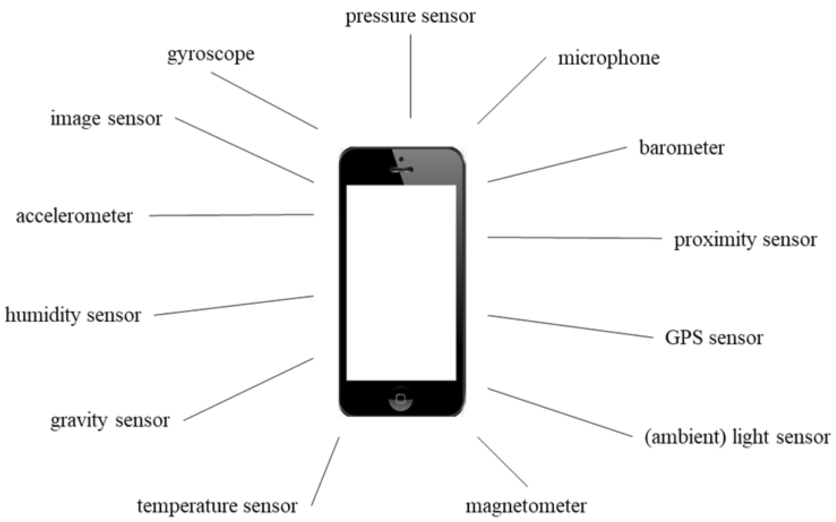
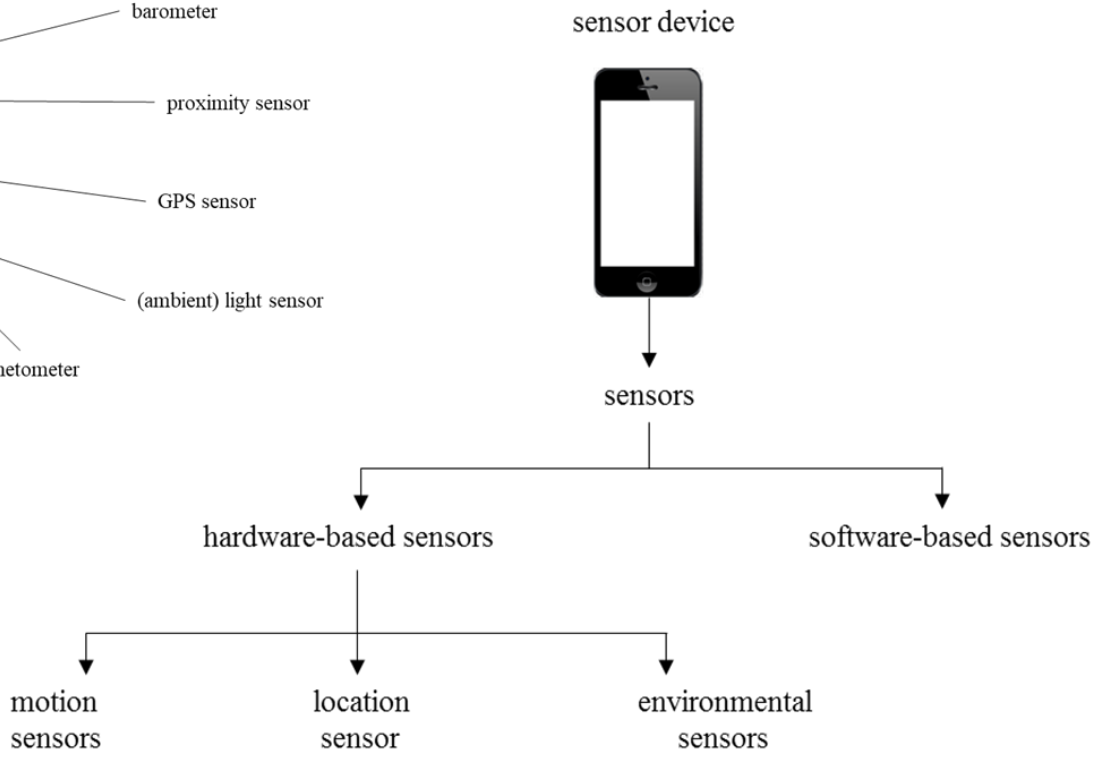
Sensors in Daily Living





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- Stress Management Score
- EDA Scan App
- Reflection
- Fitbit ECG App
- Oxygen Saturation (SpO2) Monitoring
- On-Wrist Skin Temperature Sensor
- Free Fitbit Premium™ Trial
- High & Low Heart Rate Notifications
- 24/7 Heart Rate Tracking with PurePulse® 2.0
- Heart Rate Zones
- Breathing Rate
- Heart Rate Variability
- Menstrual Health Tracking

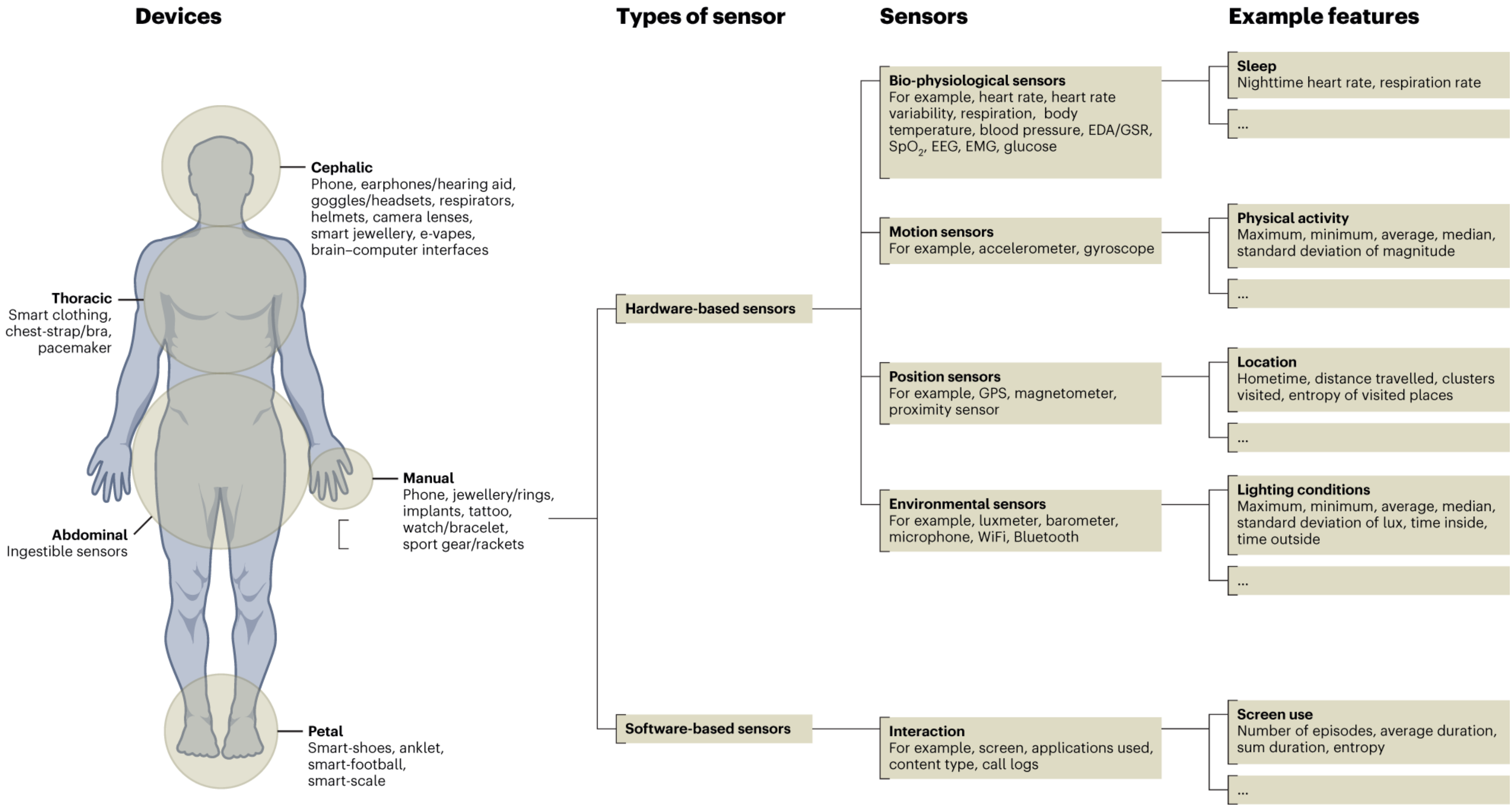
Measured During Day

- Activity Levels
- Calories
- Steps
- Inactive Times
- Naps

Measured During Sleep

- Resting Heart Rate
- Heart Rate Variability (HRV)
- Respiratory Rate
- Body Temperature
- Light, Deep and REM Sleep
- Nighttime Movement
- Sleep Timing and Quality

Smart Sensing: Process



Seiferth, C., Vogel, L., Aas, B. *et al.* How to e-mental health: a guideline for researchers and practitioners using digital technology in the context of mental health. *Nat. Mental Health* **1**, 542–554 (2023). https://doi.org/10.1038/s44220-023-00085-1

Smart Sensing

… is a process using

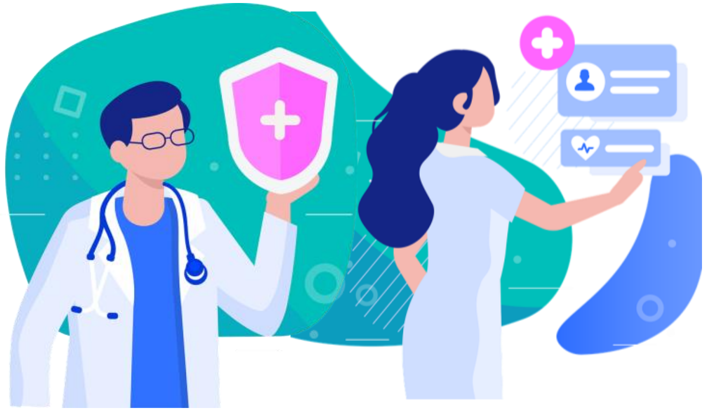
- unobtrusive sensor data / aggregated features (e.g., location, language, app usage, etc.)

+

- Optional: active data input (e.g., ecological momentary assessment)

➔ Real-time inference to (mental) health

Garatva, P., Terhorst, Y., Messner, E.-M., Karlen, W., Pryss, R., Baumeister, H., 2022. Smart Sensors for Health Research and Improvement, in: Montag, C., Baumeister, H. (Eds.), Digital Phenotyping and Mobile Sensing. Springer, Berlin.



Does this work in the context of mental health?

ORIGINAL RESEARCH article
Front. Psychiatry, 28 January 2021 | https://doi.org/10.3389/fpsyt.2021.625247

Predicting Symptoms of Depression and Anxiety Using Smartphone and Wearable Data

Isaac Moshe[1*], **Yannik Terhorst**[2,3], **Kennedy Opoku Asare**[4], **Lasse Bosse Sander**[5], **Denzil Ferreira**[4], **Harald Baumeister**[3], **David C. Mohr**[6] and **Laura Pulkki-Råback**[1]

[1]Department of Psychology and Logopedics, Faculty of Medicine, University of Helsinki, Helsinki, Finland
[2]Department of Research Methods, Ulm University, Ulm, Germany
[3]Department of Clinical Psychology and Psychotherapy, Institute of Psychology and Education, Ulm University, Ulm, Germany
[4]Center for Ubiquitous Computing, University of Oulu, Oulu, Finland
[5]Department of Rehabilitation Psychology and Psychotherapy, Institute of Psychology, University of Freiburg, Freiburg, Germany
[6]Department of Preventive Medicine, Center for Behavioral Intervention Technologies, Northwestern University, Chicago, IL, United States

Background: Depression and anxiety are leading causes of disability worldwide but often remain undetected and untreated. Smartphone and wearable devices may offer a unique source of data to detect moment by moment changes in risk factors associated with mental disorders that overcome many of the limitations of traditional screening methods.

Objective: The current study aimed to explore the extent to which data from smartphone and wearable devices could predict symptoms of depression and anxiety.

Methods: A total of $N = 60$ adults (ages 24–68) who owned an Apple iPhone and Oura Ring were recruited online over a 2-week period. At the beginning of the study, participants installed the *Delphi* data acquisition app on their smartphone. The app continuously monitored participants' location (using GPS) and smartphone usage behavior (total usage time and frequency of use). The Oura Ring provided measures related to activity (step count and metabolic equivalent for task), sleep (total sleep time, sleep onset latency, wake after sleep onset and time in bed) and heart rate variability (HRV). In addition, participants were prompted to report their daily mood (valence and arousal). Participants completed self-reported assessments of depression, anxiety and stress (DASS-21) at baseline, midpoint and the end of the study.

Method

- Longitudinal observation study: 30 days
- European-wide recruitment

- Sensing components:
  - AWARE App (iOS): Smartphone usage, Location
  - OURA-Ring: Biophysiological data (steps, sleep time, etc.)
- EMA: Daily valence and arousal (3-times a day)
- Mental Health: DASS-21 (Depression, Anxiety, Stress)

- Multilevel regression models combining data sources

Results

- N=60
- Age: M=42.8 (SD=11.6)
- Gender: 55% female
- Mostly employed (~70%)
- Highly educated (only 20% below B.Sc.)

Depression	3.78 (3.48)	–
Normal	67.3%	37
Mild	12.7%	7
Moderate	12.7%	7
Severe	5.5%	3
Extremely severe	1.8%	1

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Regression

Model	Fixed effects					Goodness of fit and Comparison*		
	Estimate	SE	*t*-value	Df	*p*-value	F	df1, df2	*P*-value
Baseline model								
Intercept	0	0.13	0	105	> 0.999			
EMA model								
Intercept	0	0.11	0.00	104	> 0.999	10.52	1, 172	0.001[a]
Valence	−0.39	0.11	−3.49	55	0.001			
GPS model								
Intercept	0	0.12	0	104	> 0.999	4.574751	1, 568	0.033[a]
Variance	−0.21	0.10	−2.15	81	0.035			
Extended digital phenotyping model: GPS and wearable data								
Intercept	0	0.11	0.00	103	> 0.999	5.23	1, 136	0.024[b]
Variance	−0.21	0.10	−2.17	78	0.033			
Time in bed	0.25	0.10	2.43	58	0.018			
Combined model: EMA and digital phenotyping model								
Intercept	0	0.10	0.00	102	> 0.999	11.47	1, 176	0.001[c]
Variance	−0.21	0.09	−2.32	72	0.023	5.42	2, 560	0.005[d]
Time in bed	0.24	0.09	2.54	59	0.014			
Arousal	−0.38	0.10	−3.61	52	0.001			

**For more details on the likelihood ratio test see chapter 5.3.1 in Van Buuren (66). [a]Comparison against baseline, [b]Comparison against GPS, [c]Comparison against extended sensing model. [d]Comparison against EMA model.*

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Conclusion

- Relationship between smart sensing features and mental health
- Combination of sensor features and EMA yielded the best prediction for mental health (i.e., depression & anxiety)

➔Augmenting existing psychodiagnostics tools by smart sensing

➔Are these associations & findings robust?

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➔**Are these associations & findings robust?**

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Currently submitted to: Journal of Medical Internet Research
Date Submitted: Sep 11, 2023

Tweet

Preprint

The Relation between passively collected GPS features and depressive symptoms: A systematic review and meta-analysis.

Yannik Terhorst; Johannes Knauer; Paula Philippi; Harald Baumeister

ABSTRACT

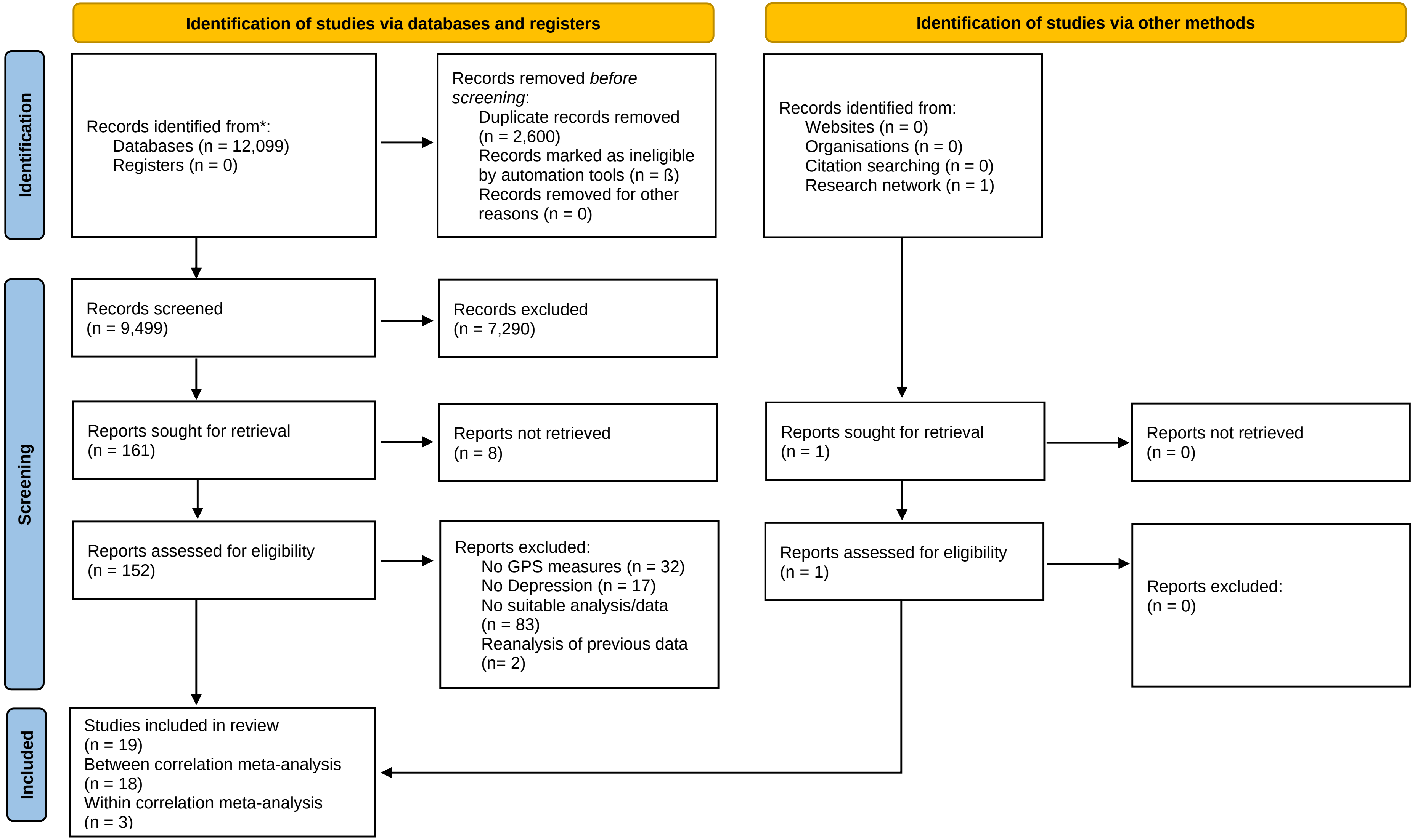
Background:

Objective unobtrusively collected GPS features (e.g., homestay, distance) from everyday devices like smartphones may offer a promising augmentation to current assessment tools for depression. However, to date there is no systematic and meta-analytical evidence on the associations between GPS features and depression.

Objective:

The present systematic review with meta-analysis investigated the between-person and within-person correlations between GPS features and depressive symptoms. Furthermore, it critically reviews the quality and potential publication bias in the field.

Results


Identification of studies via databases and registers
Identification of studies via other methods
Identification
Records identified from*:
Databases (n = 12,099)
Registers (n = 0)
Records removed *before screening*:
Duplicate records removed (n = 2,600)
Records marked as ineligible by automation tools (n = ß)
Records removed for other reasons (n = 0)
Records identified from:
Websites (n = 0)
Organisations (n = 0)
Citation searching (n = 0)
Research network (n = 1)
Screening
Records screened (n = 9,499)
Records excluded (n = 7,290)
Reports sought for retrieval (n = 161)
Reports not retrieved (n = 8)
Reports sought for retrieval (n = 1)
Reports not retrieved (n = 0)
Reports assessed for eligibility (n = 152)
Reports excluded:
No GPS measures (n = 32)
No Depression (n = 17)
No suitable analysis/data (n = 83)
Reanalysis of previous data (n= 2)
Reports assessed for eligibility (n = 1)
Reports excluded:
(n = 0)
Included
Studies included in review (n = 19)
Between correlation meta-analysis (n = 18)
Within correlation meta-analysis (n = 3)

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Results

Table 4. Pooled between-person correlations.

Feature	N	Cor	CI	Prediction Interval	I^2
circadian movement	1201	-0.36	-0.71 to 0.12	-0.91 to 0.64	86%
distance	1824	-0.25	-0.29 to -0.21	-0.30 to -0.20	0%
norm entropy	1849	-0.17	-0.29 to -0.04	-0.44 to 0.13	69%
location variance	2287	-0.17	-0.26 to -0.06	-0.36 to 0.04	58%
entropy	2254	-0.13	-0.23 to -0.04	-0.35 to 0.10	57%
n_cluster	2282	-0.11	-0.18 to -0.03	-0.25 to 0.04	36%
homestay	2216	0.10	0.00 to 0.19	-0.09 to 0.27	50%
speed moving	1266	-0.01	-0.07 to 0.06	-0.09 to 0.07	0%
time moving	748	-0.05	-0.21 to 0.11	-0.45 to 0.36	68%

Conclusion

- Relationship between smart sensing features and mental health
- Combination of sensor features and EMA yielded the best prediction for mental health (i.e., depression & anxiety)

➔Augmenting existing psychodiagnostics tools by smart sensing

➔Are these associations & findings robust?

➔**Lessons learned: Smart sensing data is complex!**

Predicting Depression From Smartphone Behavioral Markers Using Machine Learning Methods, Hyperparameter Optimization, and Feature Importance Analysis: Exploratory Study

Kennedy Opoku Asare [1]; Yannik Terhorst [2]; Julio Vega [3]; Ella Peltonen [1]; Eemil Lagerspetz [4]; Denzil Ferreira [1]

Article | Authors | Cited by | Tweetations (5) | Metrics

Abstract

Background:
Depression is a prevalent mental health challenge. Current depression assessment methods using self-reported and clinician-administered questionnaires have limitations. Instrumenting smartphones to passively and continuously collect moment-by-moment data sets to quantify human behaviors has the potential to augment current depression assessment methods for early diagnosis, scalable, and longitudinal monitoring of depression.

Objective:
The objective of this study was to investigate the feasibility of predicting depression with human

Results

- N=629

Table 5. Average and standard deviations of Accuracy, Precision, Recall, F1, AUC and Cohen's Kappa metrics for 10 fold cross validation, with features only dataset as predictors

Metric, mean % (SD)	RF[a]	XGB[b]	SVM[c]	LR[d]	KNN[e]
Accuracy	97.97 (0.37)	98.14 (0.37)	85.68 (1.16)	59.27 (1.45)	96.44 (0.52)
Precision	92.50 (1.78)	92.51 (1.25)	51.98 (2.58)	20.29 (1.25)	85.55 (1.97)
Recall	94.38 (1.86)	95.56 (1.99)	80.67 (2.36)	57.25 (4.14)	92.19 (2.24)
F1	93.41 (1.19)	94.00 (1.21)	63.20 (2.29)	29.95 (1.87)	88.73 (1.63)
AUC	98.83 (0.67)	99.06 (0.54)	89.47 (1.06)	62.43 (2.22)	94.69 (1.15)
Cohen's Kappa	92.21 (1.41)	92.90 (1.43)	54.83 (2.92)	9.66 (2.38)	86.61 (1.93)

[a] RF: Random Forest
[b] XGB: XGBoost
[c] SVM: Support Vector Machine
[d] LR: Logistic Regression
[e] KNN: K-Nearest Neighbor

Conclusion

- ML well-suited for complex smart sensing data
  - Especially: ML capable of handling non-linear relationships

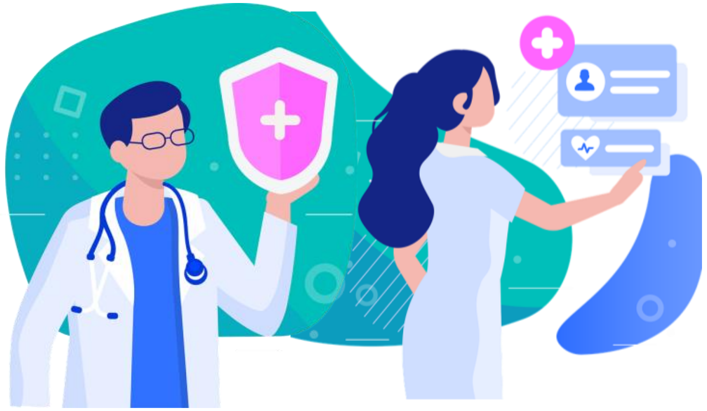
- Combination of smart sensing and ML may lead to promising psychodiagnostics (support-) tools in future

Chapter 24
Smart Sensing Enhanced Diagnostic Expert Systems

Yannik Terhorst, Johannes Knauer, and Harald Baumeister

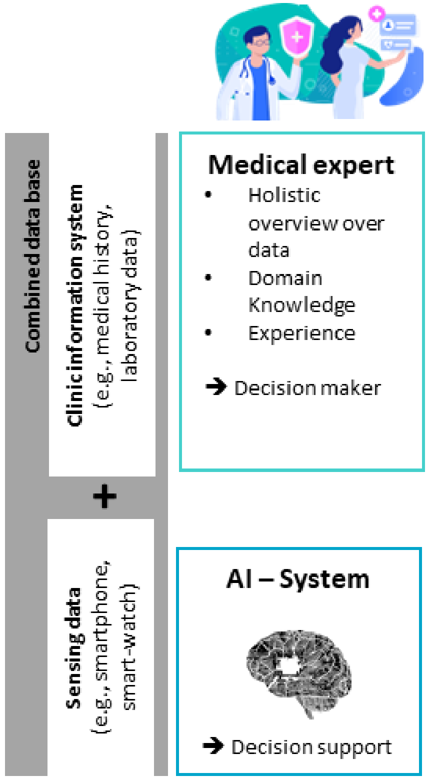
Abstract The ubiquitous presence of sensors (e.g., in smartphones) in our everyday life allows a constant real-time collection of data. This data has been successfully used in diagnosis and prediction of health outcomes and has the potential to improve health care. However, with data security and accountability as core requirements of medical applications, it remains a major challenge to integrate smart sensing information into the health care systems. One promising application is the integration into expert systems, in which smart sensing information is used to assist medical experts in their decisions. The present chapter aims to introduce expert systems, outline conceptual examples of such a smart sensing enhanced expert system, and summarize the evidence for smart sensing enhanced expert systems in health care. Lastly, the chapter will be concluded by discussing challenges in the field including ethical, privacy and security, and clinical issues followed by an outlook about future directions and developments.

Keywords Digital phenotyping · Smart sensing · Expert system

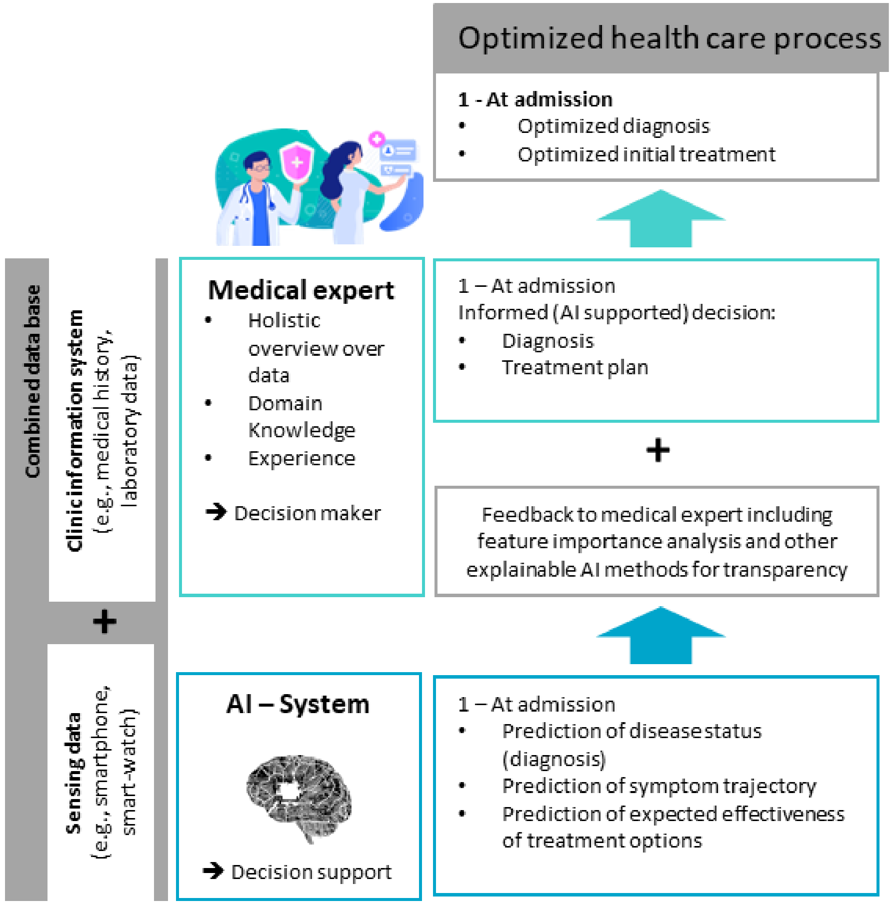


Implementation in clinical practice

Example


Combined data base
Clinic information system
(e.g., medical history, laboratory data)
+
Sensing data
(e.g., smartphone, smart-watch)
Medical expert
• Holistic overview over data
• Domain Knowledge
• Experience
→ Decision maker
AI – System
→ Decision support

Example


Optimized health care process
1 - At admission
• Optimized diagnosis
• Optimized initial treatment
Combined data base
Clinic information system
(e.g., medical history, laboratory data)
+
Sensing data
(e.g., smartphone, smart-watch)
Medical expert
• Holistic overview over data
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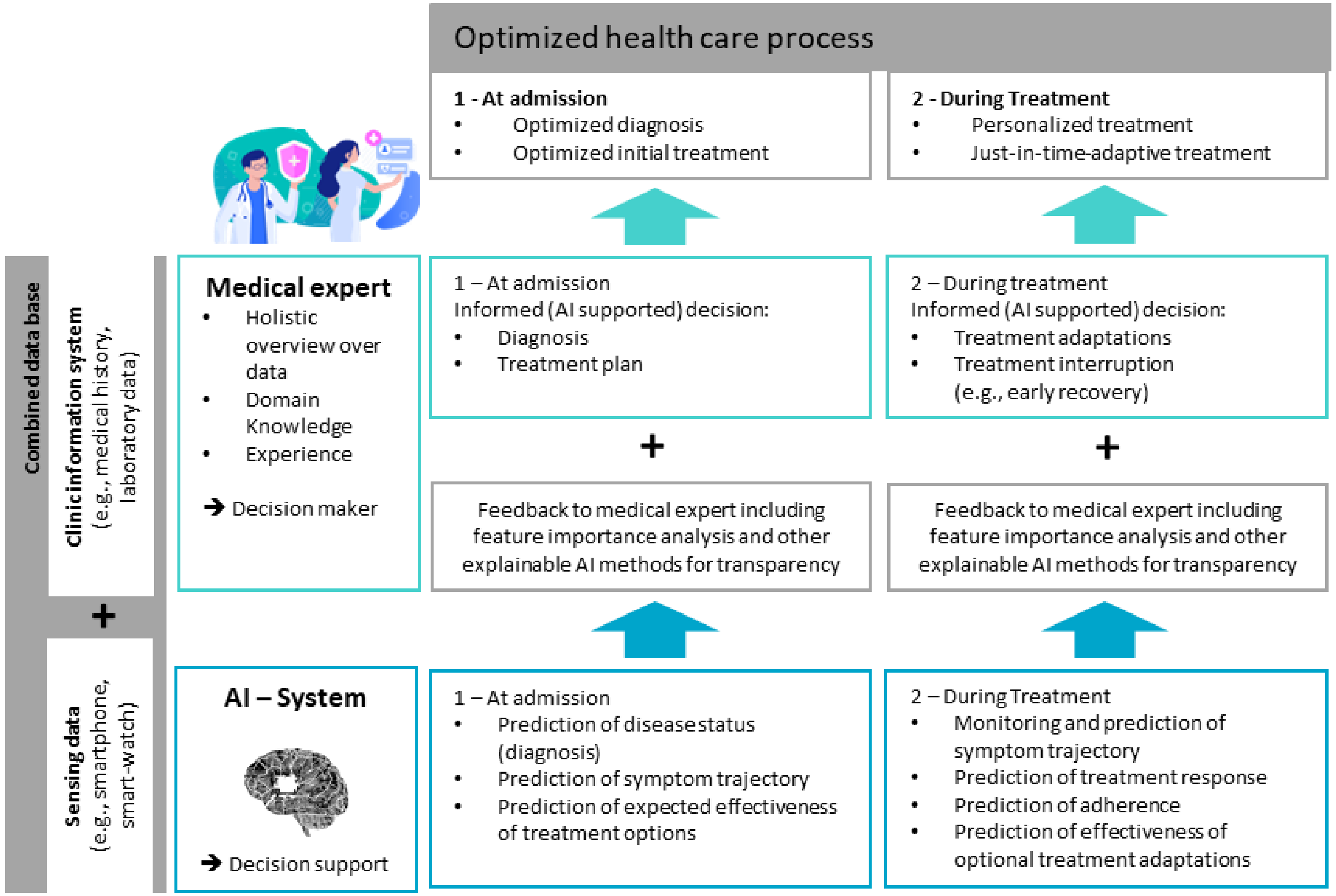
• Experience
→ Decision maker
AI – System
→ Decision support
1 – At admission
Informed (AI supported) decision:
• Diagnosis
• Treatment plan
+
Feedback to medical expert including feature importance analysis and other explainable AI methods for transparency
1 – At admission
• Prediction of disease status (diagnosis)
• Prediction of symptom trajectory
• Prediction of expected effectiveness of treatment options

Example


Optimized health care process
1 - At admission
• Optimized diagnosis
• Optimized initial treatment
2 - During Treatment
• Personalized treatment
• Just-in-time-adaptive treatment
Combined data base
Clinic information system
(e.g., medical history, laboratory data)
+
Sensing data
(e.g., smartphone, smart-watch)
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→ Decision maker
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• Diagnosis
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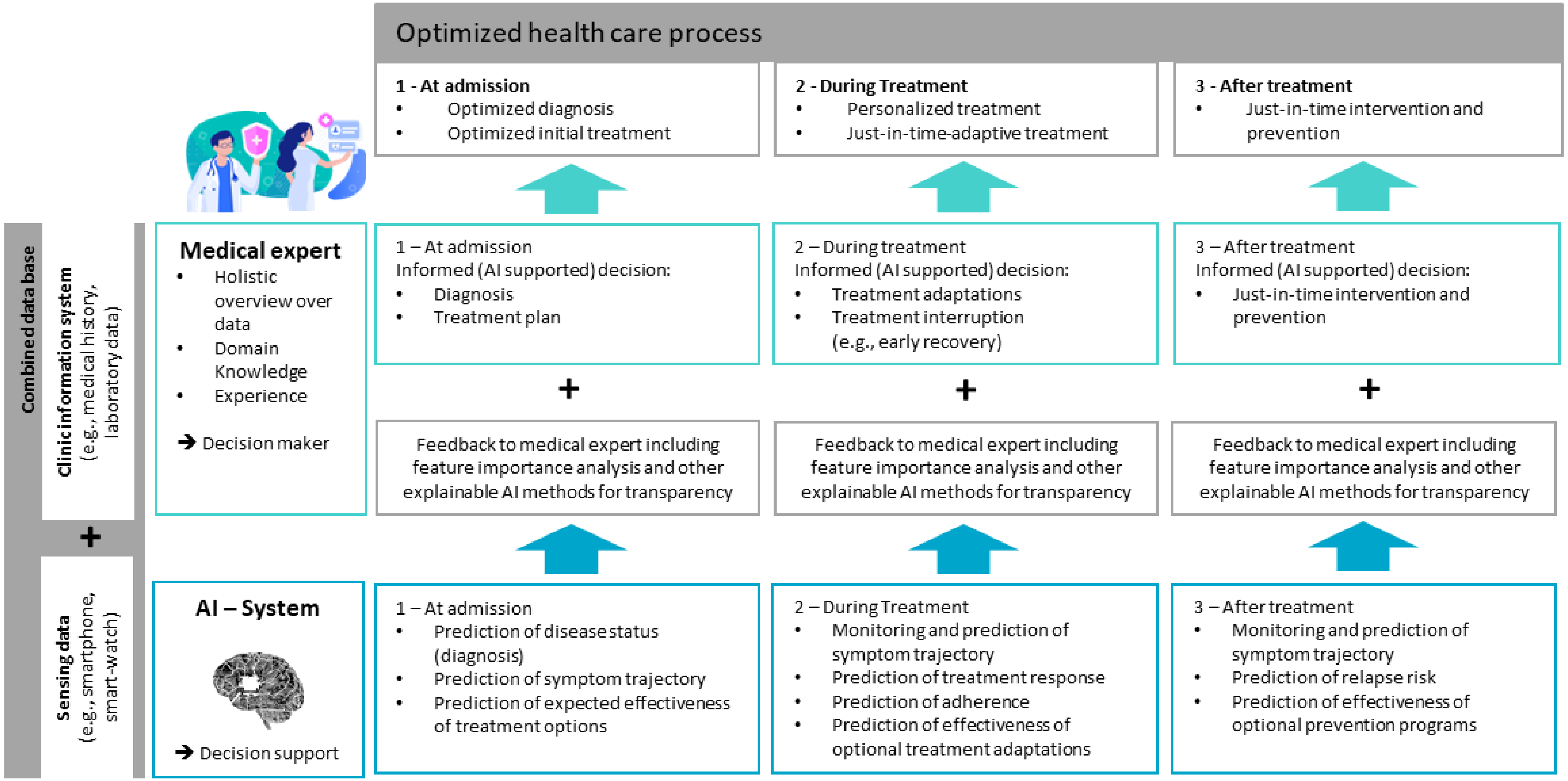
2 – During treatment
Informed (AI supported) decision:
• Treatment adaptations
• Treatment interruption (e.g., early recovery)
+
+
Feedback to medical expert including feature importance analysis and other explainable AI methods for transparency
Feedback to medical expert including feature importance analysis and other explainable AI methods for transparency
AI – System
→ Decision support
1 – At admission
• Prediction of disease status (diagnosis)
• Prediction of symptom trajectory
• Prediction of expected effectiveness of treatment options
2 – During Treatment
• Monitoring and prediction of symptom trajectory
• Prediction of treatment response
• Prediction of adherence
• Prediction of effectiveness of optional treatment adaptations

Example


Optimized health care process
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2 - During Treatment
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• Just-in-time-adaptive treatment
3 - After treatment
• Just-in-time intervention and prevention
Combined data base
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→ Decision maker
1 – At admission
Informed (AI supported) decision:
• Diagnosis
• Treatment plan
2 – During treatment
Informed (AI supported) decision:
• Treatment adaptations
• Treatment interruption (e.g., early recovery)
3 – After treatment
Informed (AI supported) decision:
• Just-in-time intervention and prevention
+
Feedback to medical expert including feature importance analysis and other explainable AI methods for transparency
AI – System
→ Decision support
1 – At admission
• Prediction of disease status (diagnosis)
• Prediction of symptom trajectory
• Prediction of expected effectiveness of treatment options
2 – During Treatment
• Monitoring and prediction of symptom trajectory
• Prediction of treatment response
• Prediction of adherence
• Prediction of effectiveness of optional treatment adaptations
3 – After treatment
• Monitoring and prediction of symptom trajectory
• Prediction of relapse risk
• Prediction of effectiveness of optional prevention programs

Challenges (and future cooperations?)

- Does it work in children and adolescents?
- What would promising prediction-targets be in expert systems?
    - Risk
    - Response
    - Deterioration/early-Warning
    - Symptoms
    - Symptom networks
- What is the acceptance?
    - Youth’s perspective
    - Parents’ perspective
    - Clinicians’ perspective

Further Reading

Consensus Statement | Published: 07 August 2023

How to e-mental health: a guideline for researchers and practitioners using digital technology in the context of mental health

Caroline Seiferth, Lea Vogel, Benjamin Aas, Isabel Brandhorst, Per Carlbring, Annette Conzelmann, Narges Esfandiari, Marlene Finkbeiner, Karsten Hollmann, Heinrich Lautenbacher, Edith Meinzinger, Alexandra Newbold, Ansgar Opitz, Tobias J. Renner, Lasse Bosse Sander, Philip S. Santangelo, Ramona Schoedel, Björn Schuller, Clemens Stachl, sysTelios Think Tank, Yannik Terhorst, John Torous, Katarzyna Wac, Aliza Werner-Seidler, ... Johanna Löchner + Show authors

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Acceptance of smart sensing: a barrier to implementation—results from a randomized controlled trial

Yannik Terhorst[1]*, Nadine Weilbacher[1], Carolin Suda[2], Laura Simon[1], Eva-Maria Messner[1], Lasse Bosse Sander[3] and Harald Baumeister[1]

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Review > Harv Rev Psychiatry. 2021 Nov-Dec;29(6):401-408.
doi: 10.1097/HRP.0000000000000310.

Digital Phenotyping in Child and Adolescent Psychiatry: A Perspective

Melanie Nisenson [1], Vanessa Lin, Meredith Gansner

Affiliations + expand

PMID: 34313626 DOI: 10.1097/HRP.0000000000000310

universität ulm

Thank you for attention & a big thank you to our Sensing Team & cooperation partners


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Julius-Maximilians-UNIVERSITÄT WÜRZBURG

Questions & Discussion

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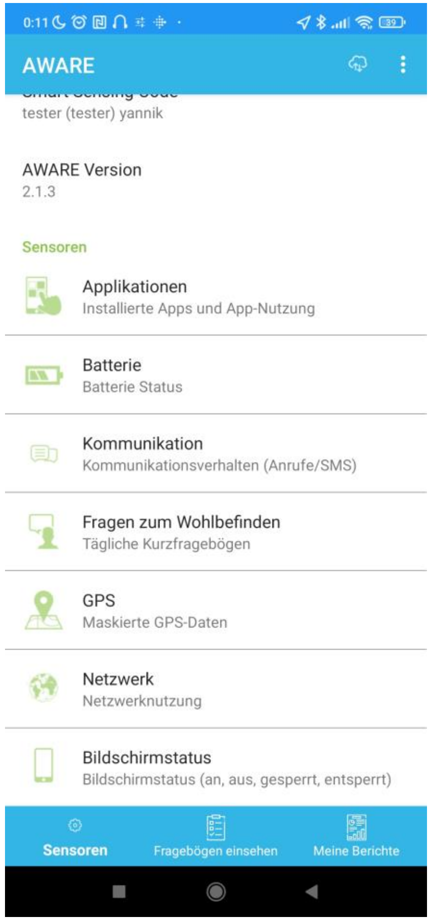
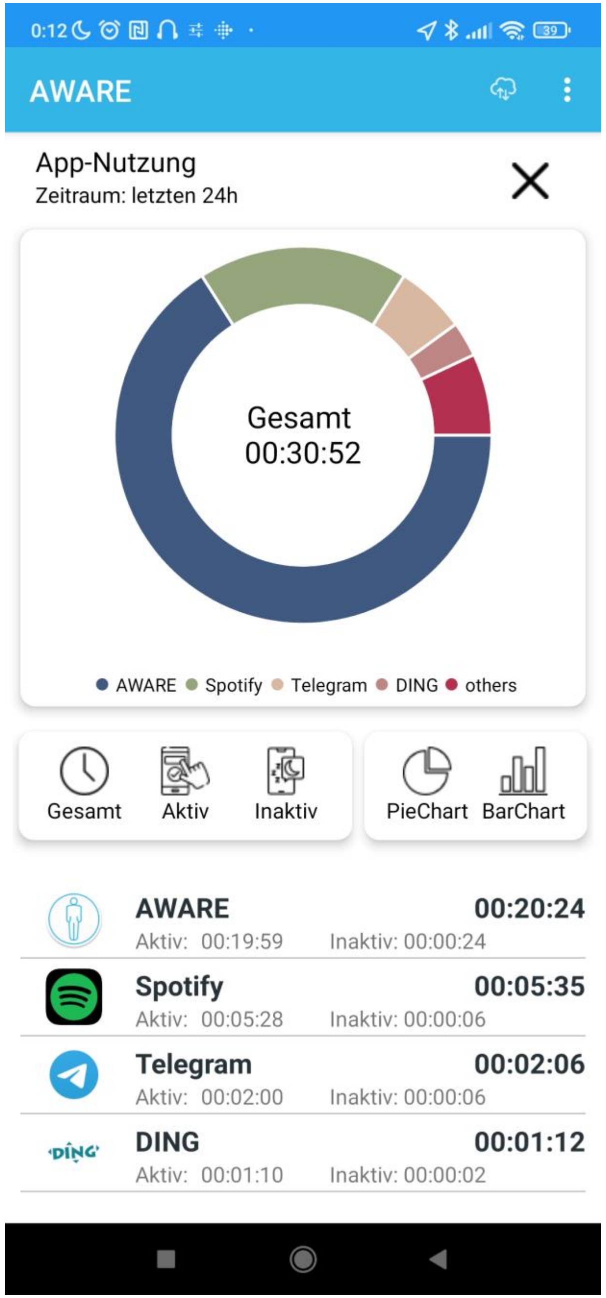
Find further research on:
Google Scholar

Sensor overview

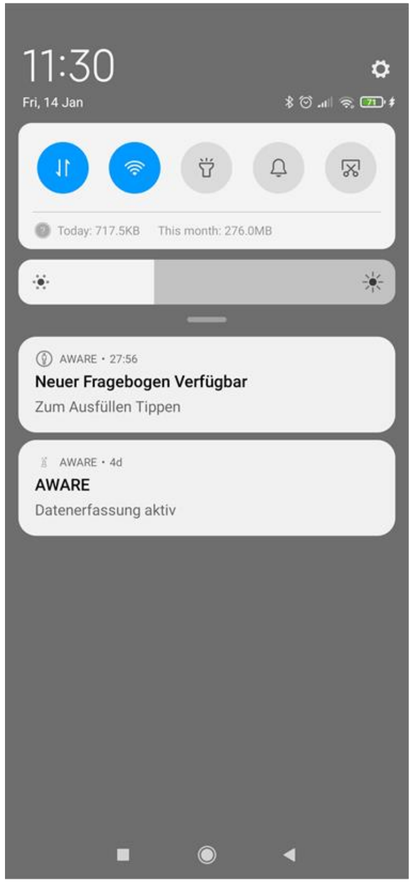


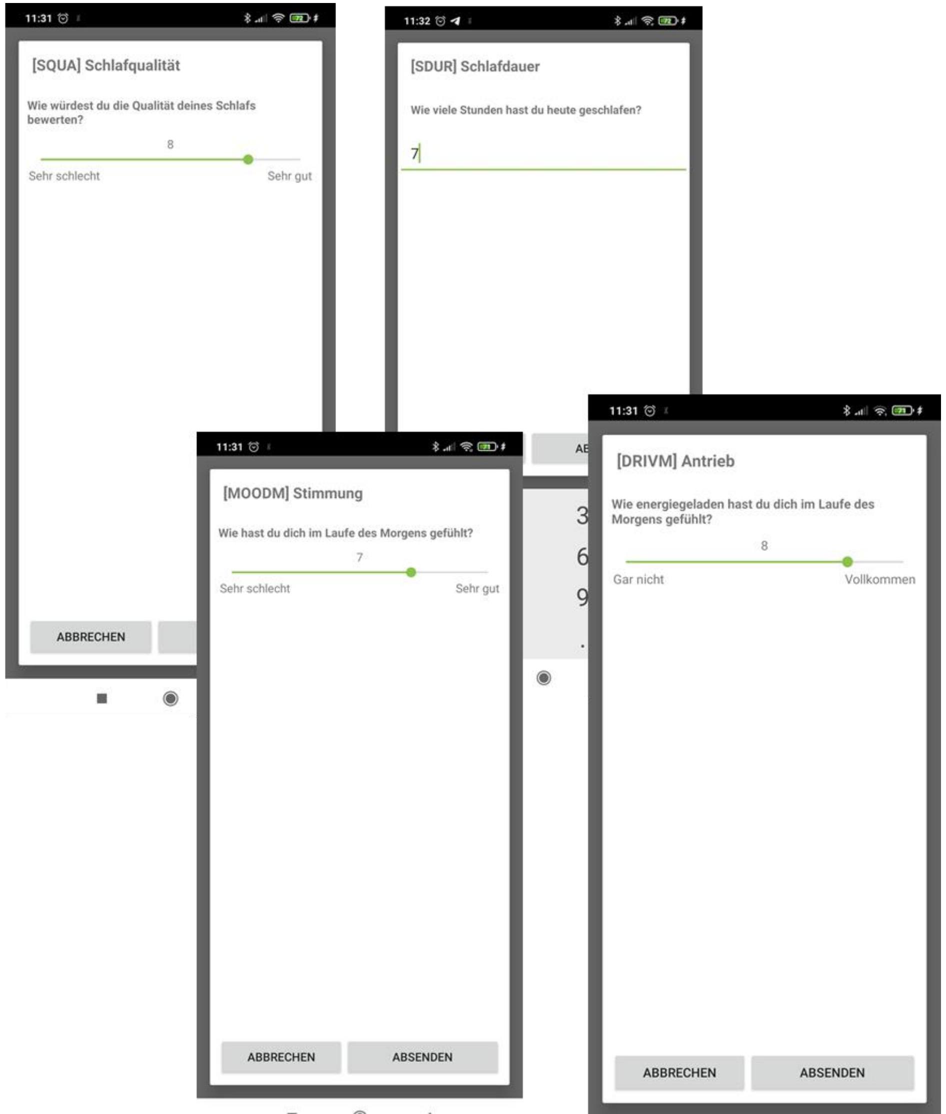
LIWC

Direct Feedback

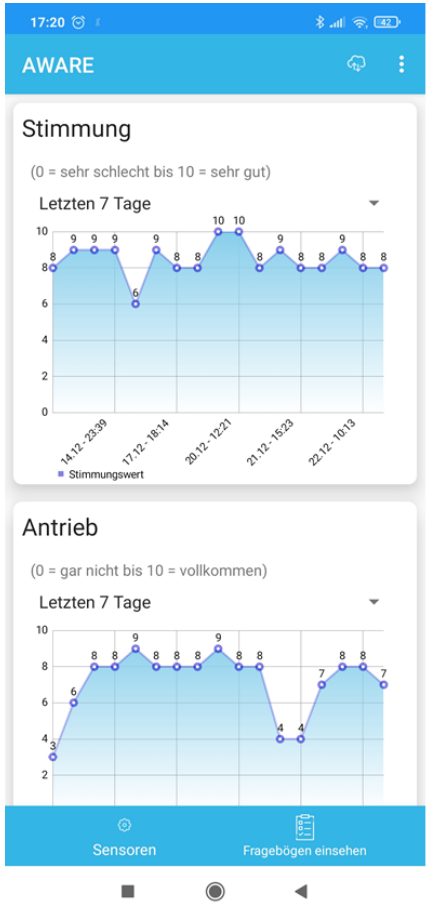


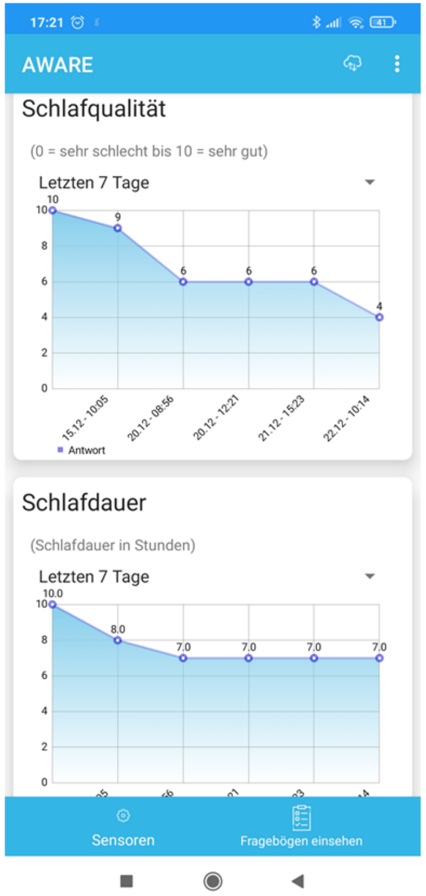
Active User Input (i.e., EMA)





Direct Feedback

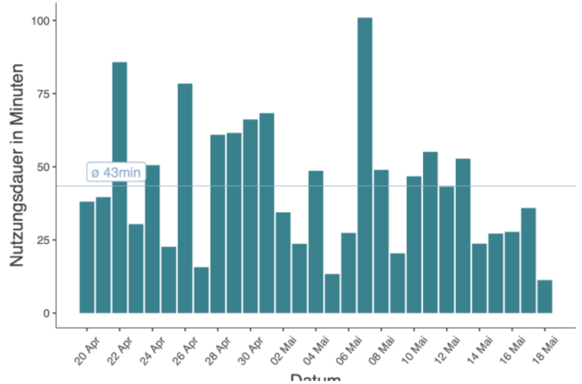


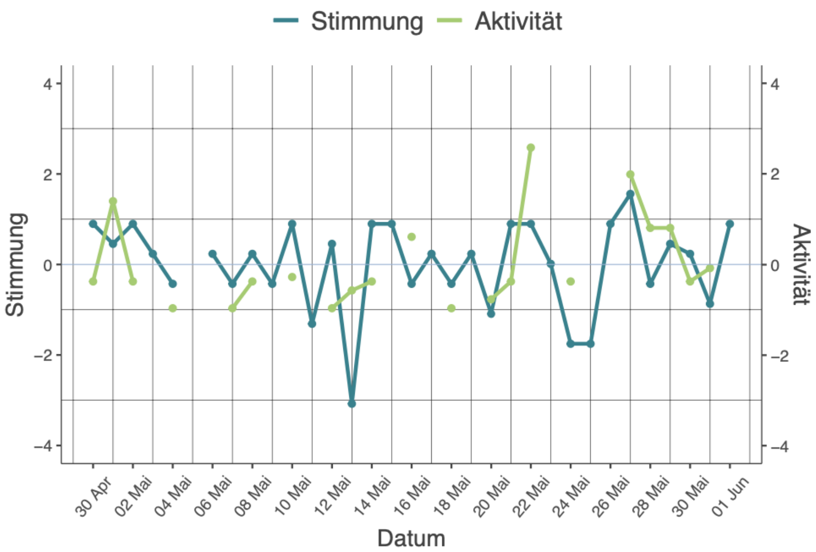


Extended Reports via Mail

Smartphone-Nutzungsdauer

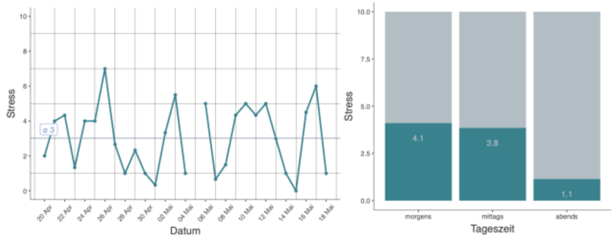
Die folgende Grafik zeigt deine tägliche Smartphone-Nutzungsdauer in Minuten. Durchschnittlich hast du dein Smartphone 43 Minuten pro Tag verwendet.





Stress

Über die App wurde 3x täglich dein Stress-Level erfragt. Das Liniendiagramm zeigt de deines täglichen Stress-Levels (von 1 bis 10). In der rechten Grafik wird dir angezeigt, wie du morgens, mittags und abends im Durchschnitt warst.



Aktivität

Die folgende Grafik zeigt deine körperliche Aktivität pro Tag.

Hinweis: Die Grafik spiegelt nur deine selbst berichteten Angaben wider.

Durchschnittlich hast du dich im letzten Monat 32 Minuten pro Tag bewegt. Die Empfehlung der Weltgesundheitsorganisation (WHO) liegt bei 30 Minuten Bewegung pro Tag. Dieses Ziel hast du im letzten Monat an 11 Tagen erreicht.