Depression monitoring via Mobile sensing

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Bayaneh Amini
1404/02/15

The Content

Depression
(definition, Clinical Dimensions and Global Burden)

Traditional Methods Of Depression Assessment
(Limitations, Necessity of Using Mobile Sensing)

Introduction To Mobile Sensing
(history and sensors function)

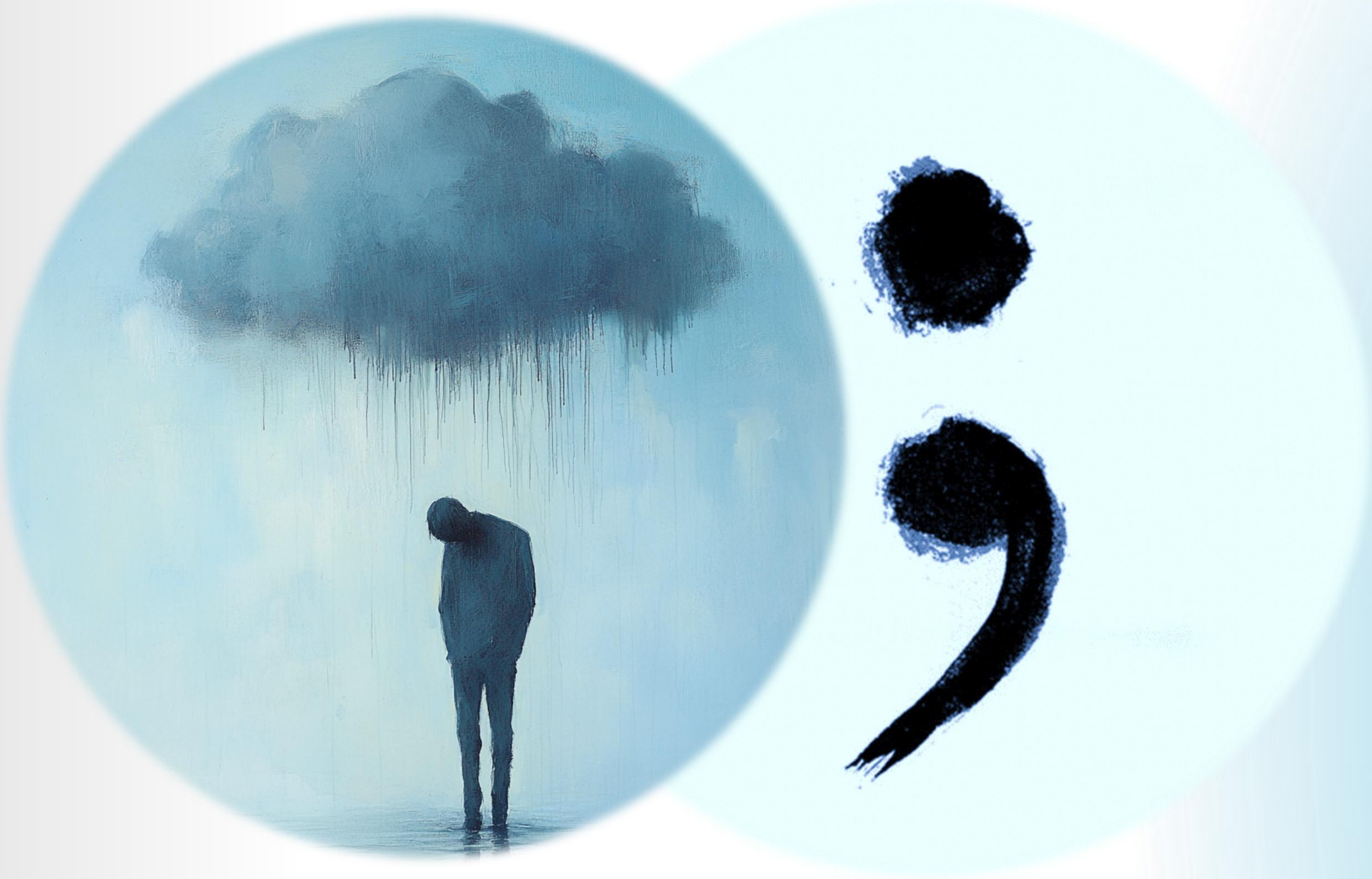
Mobile Sensors
(definition, function, feature extraction)

Mobile Sensing
(advantage, challenge)

Future of Mobile Sensing

Five Relevant Articles In This Field

Depression



Depression

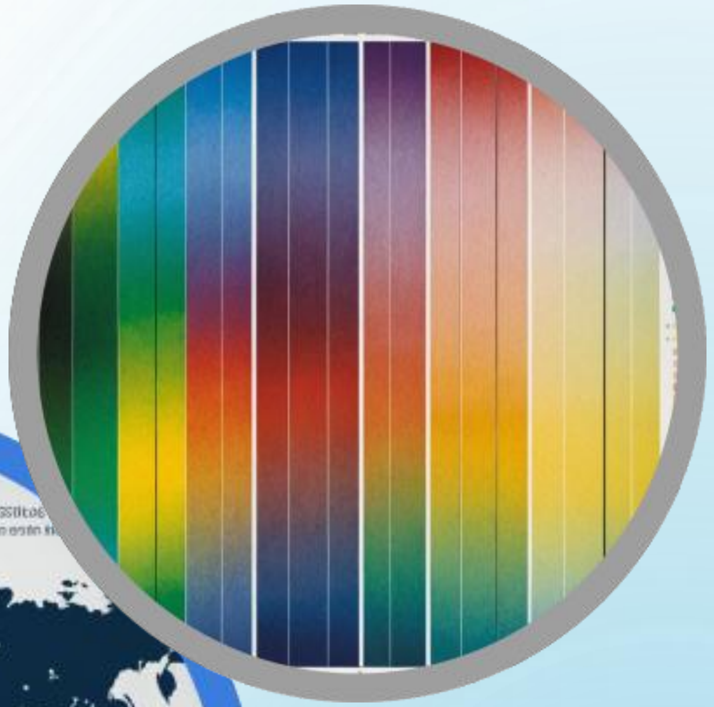
Definition

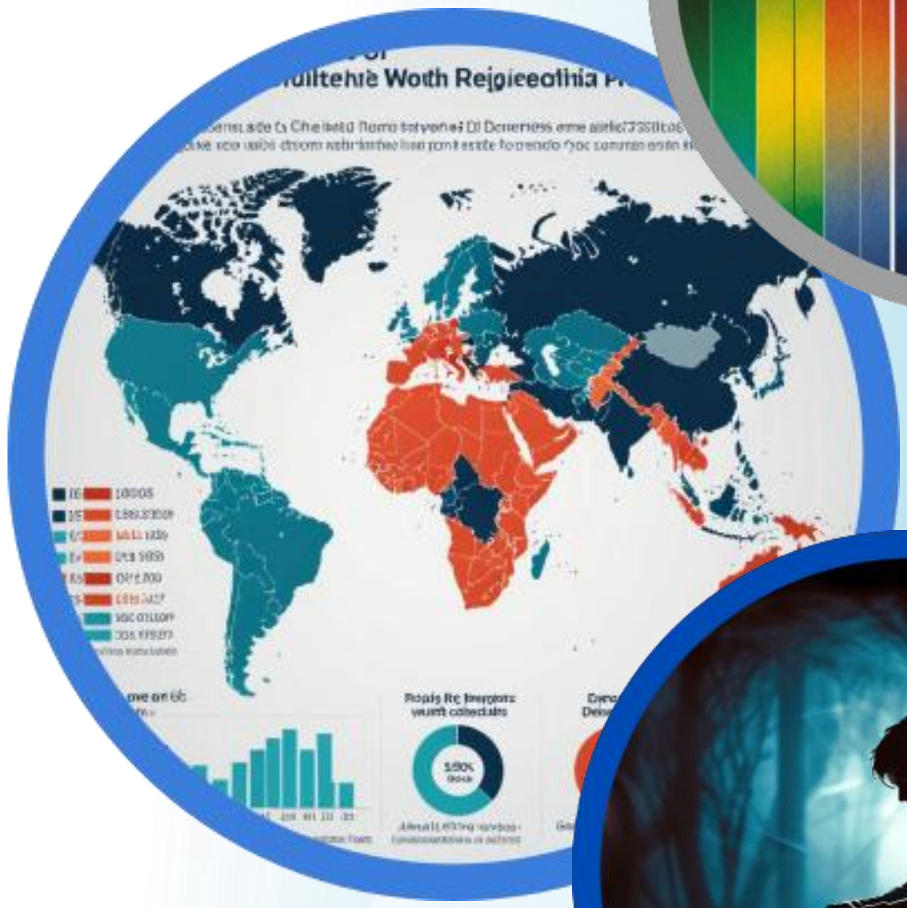
depression as a common mental disorder characterized by persistent sadness, lack of interest or pleasure in activities, disturbed sleep and appetite, fatigue, and poor concentration. Unlike normal mood fluctuations, depression can be long-lasting, recurrent, and significantly impair daily functioning. In severe cases, it may lead to suicide.

❑ Depression is a mood disorder.

❑ **Causes:**

- Combination of genetic, environmental, and life events.
- Chemical changes in the brain (neurotransmitter imbalances).





depression

Major Depressive Disorder (MDD)-DSM-5*

- **Associated Symptoms:**
  - Emotions: Persistent sadness, hopelessness, worthlessness.
  - Physical & Cognitive: Sleep and appetite changes, fatigue, concentration problems.
  - Functioning: Impairment in social and work activities.
- Duration: Symptoms persist for at least two weeks

Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition

WHO Fact Sheet on Depression

Depression statistics

2024

~280 million

People affects **5% of adults globally**

Higher impact on women than men.

700K

Die by **SUICIDE** each year worldwide (15-29)

Less than **50%** of individuals

suffering from depression receive appropriate

treatment. Limited access to treatment

WHO Fact Sheet on Depression

Burden of depression

2024

Leading Cause of Disability

- the main cause of years lived with disability worldwide.
- depression among the top ten causes of disease burden.

Impact on Quality of Life

- disrupt social, academic, and professional functioning

Increased Risk of Premature Death

- higher risk of developing physical illnesses and experiencing premature death

Economic and Social Burden

- imposes significant economic costs on healthcare systems and economies

Timely diagnosis and continuous monitoring are of great importance:

- They can prevent the progression of depression.
- They help ensure the timely provision of supportive or psychological treatments.
- They play a crucial role in reducing serious risks, such as the risk of suicide.
- They contribute to improving the individual’s quality of life and personal and social functioning.

Traditional Methods of Depression Assessment

Traditional Methods of Depression Assessment

- **Self-report questionnaires:** Individuals answer standardized sets of questions about their mood, behaviors, and thoughts.
- **Clinician-administered interviews:** Structured or semi-structured interviews conducted by mental health professionals (psychologists, psychiatrists).

Problems and Limitations of Traditional Approaches

- **Time-consuming**
- **Cost-intensive**
- **Susceptible to errors**
- **Inconsistent data**

Barriers to Seeking Psychological Help Among Individuals with Depression

- Stigma and judgment
- Misconceptions & lack of awareness
- Financial and access issues
- Depression symptoms
- Fear of medication
- Embarrassment & shame
- Fear of confronting emotions

What is the solution?

Mobile Sensing is a solution?!

- High Accessibility
- Continuous and Non-Invasive Monitoring
- Cost Reduction
- Objective and Reliable Data
- Real-World Assessment

Introduction to Mobile Sensing

Definition and Evolution

- Use of mobile devices as sensors
- Evolution from basic to advanced
- Integration with smartphones

Key Concepts

- Sensor types and capabilities
- Real-time information gathering
- Data processing on-device

Importance in Data Collection

- Ubiquitous data collection
- Cost-effective research tool
- Enables large-scale studies

History of Mobile Sensing for Depression

2000-2005
Emergence of Smartphones & Initial Sensing

2006-2009
Linking Behavior to Mental Health

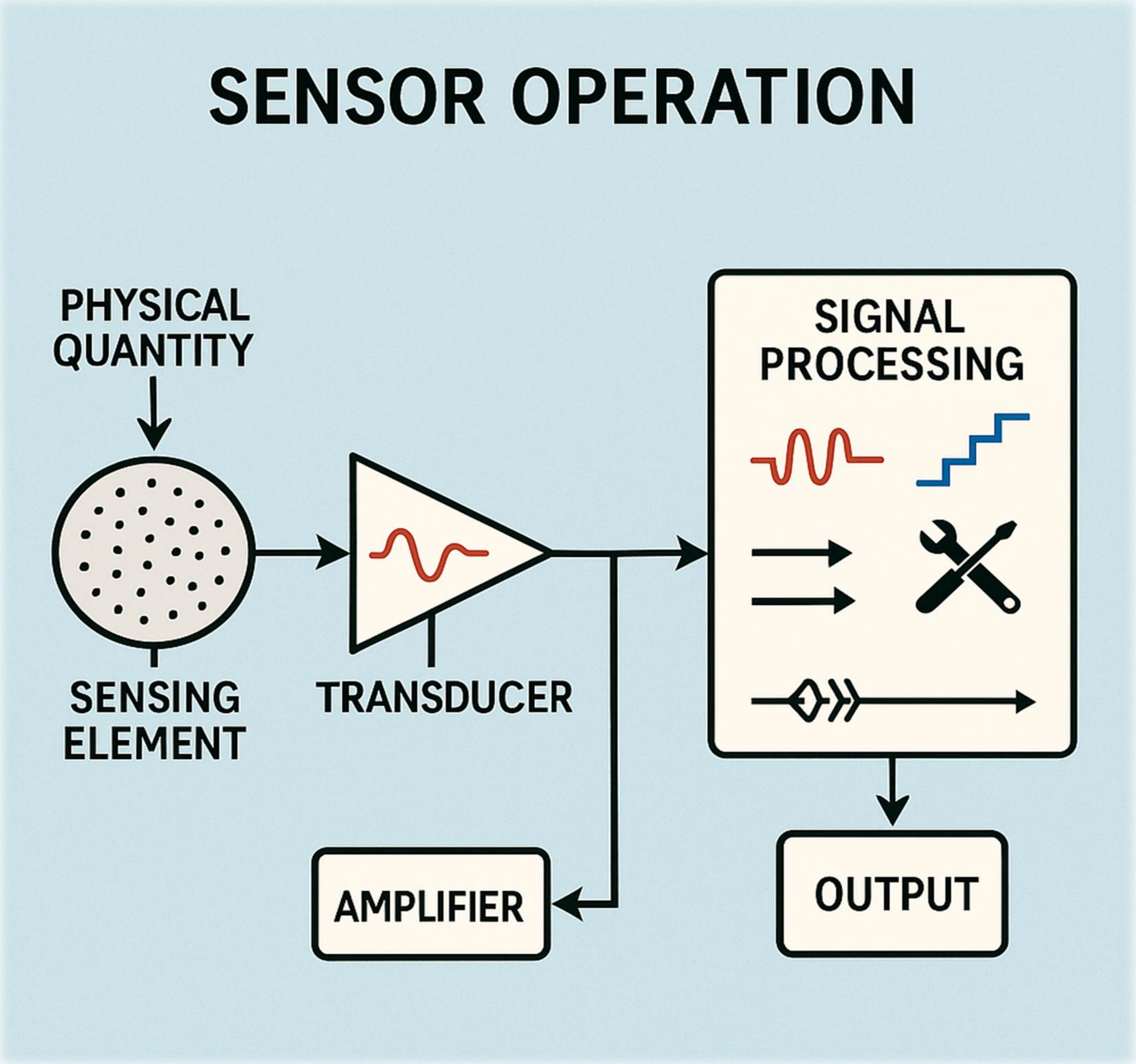
2010-2013
First Tools for Mood Monitoring

2014-2016
Focused Studies on Depression

2017-2019
Clinical Applications & Digital Interventions

2020 onwards
Expansion During Pandemic & Future Outlook

from basic tracking to a vital tool for depression detection and management



a) Sensing Element

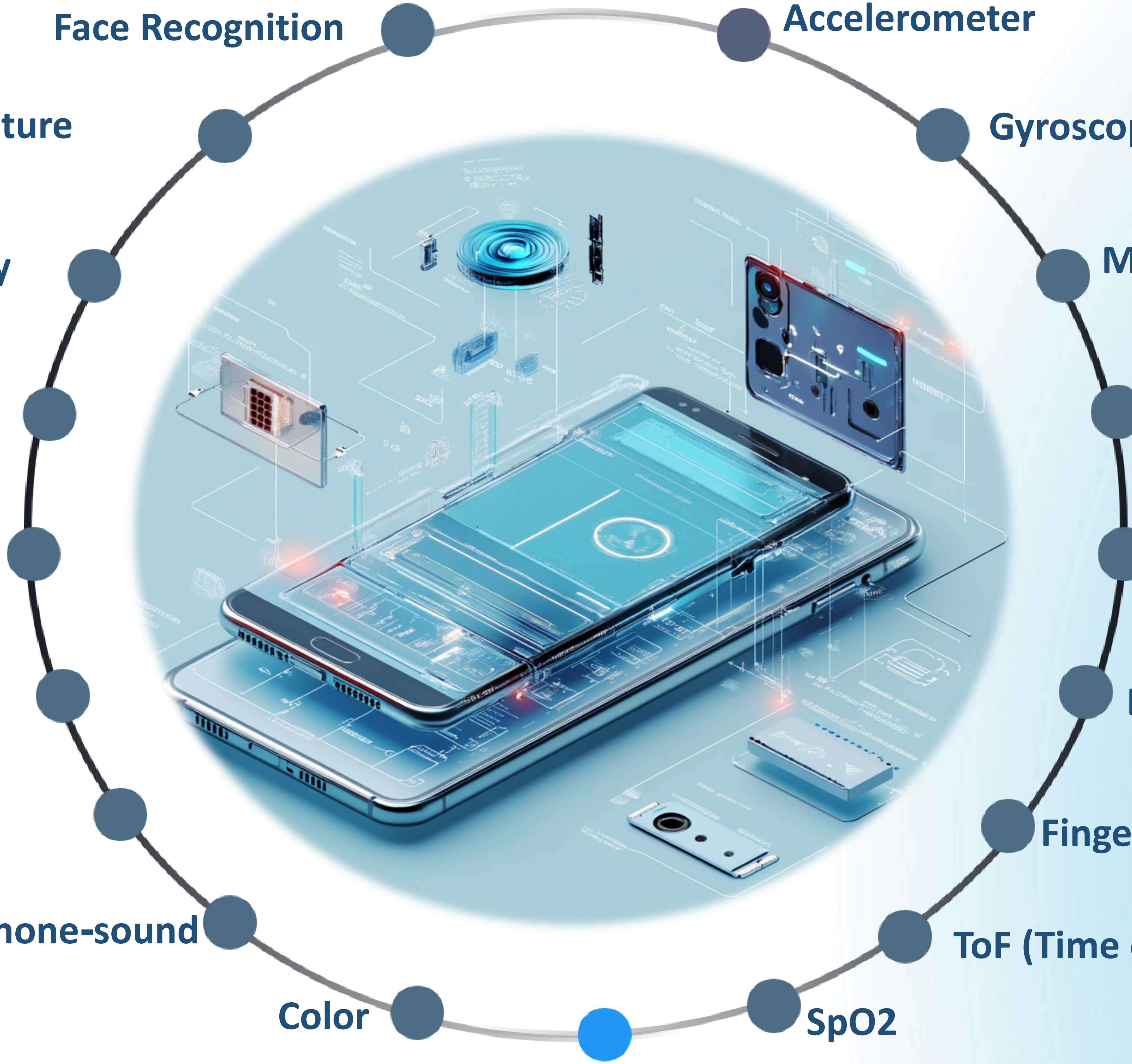
b) Transducer

c) Amplifier

d) Signal Processing Circuit

e) Output

Mobile sensors:



GPS

Definition:

Determines geographic location

Function:

It receives signals from satellites, calculating position via timing and distance from multiple satellites.

The feature’s extraction :

- Home stay
- Distance traveled
- Number of place visited
- ….

Accelerometer

Definition:

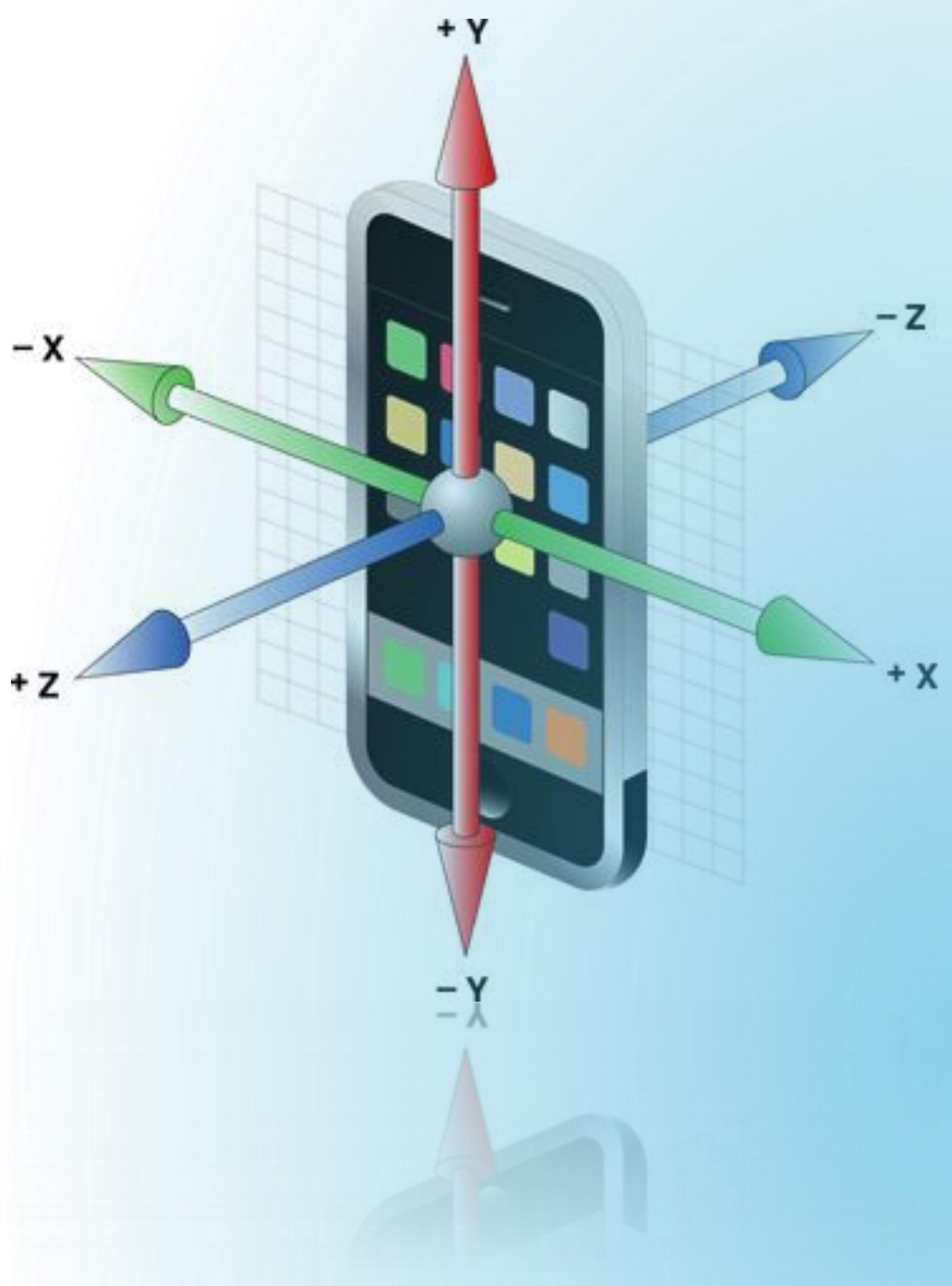
Measures acceleration in three axes (X, Y, Z) to detect motion and orientation.

Function:

It uses a small mass that moves with the phone, converting displacement into electrical signals.

The feature’s extraction :

- direction and speed at which the phone was spinning around its axis



Sound

Definition:

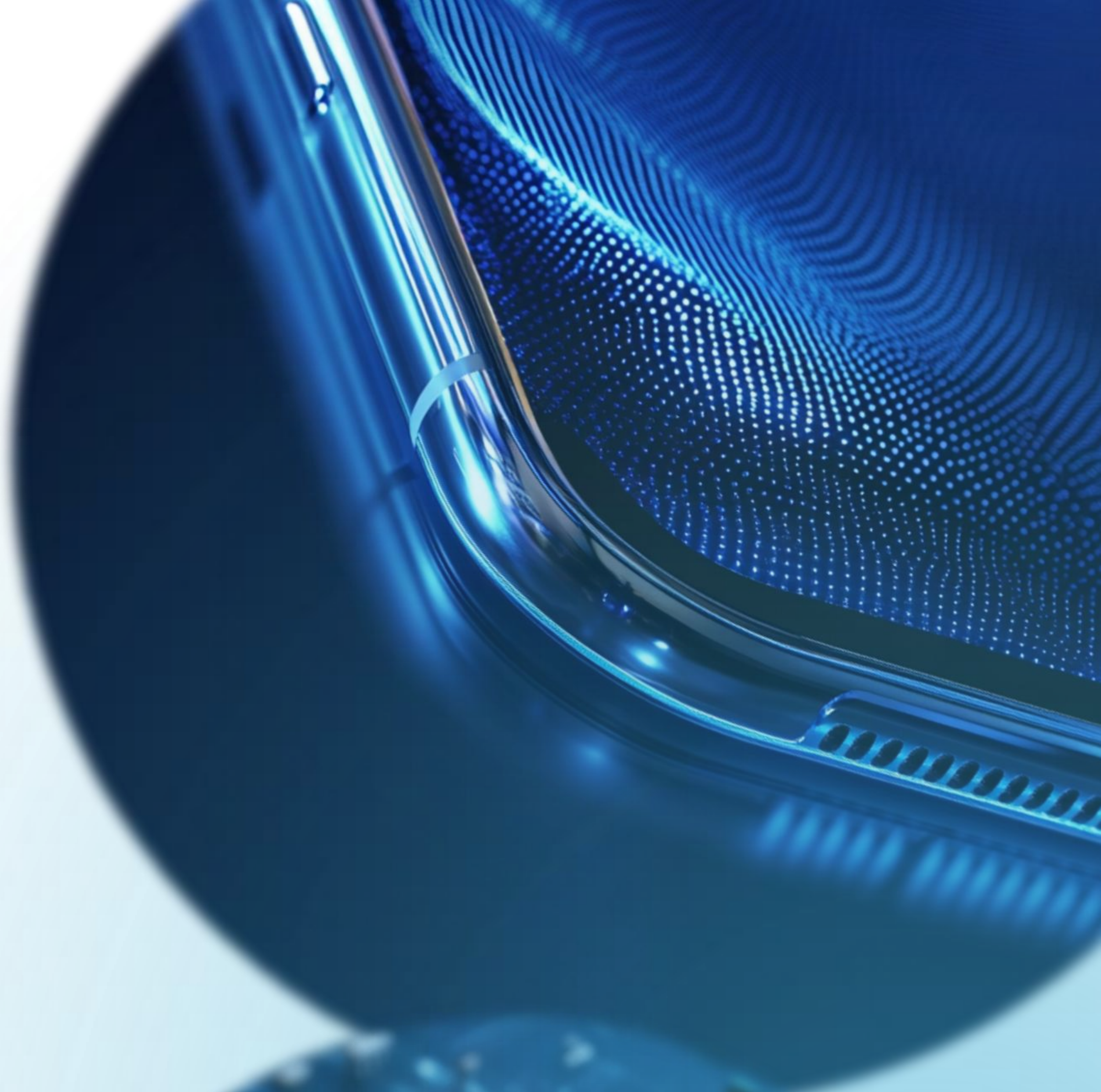
Captures sound for calls, recordings, and voice assistants in mobile phones.

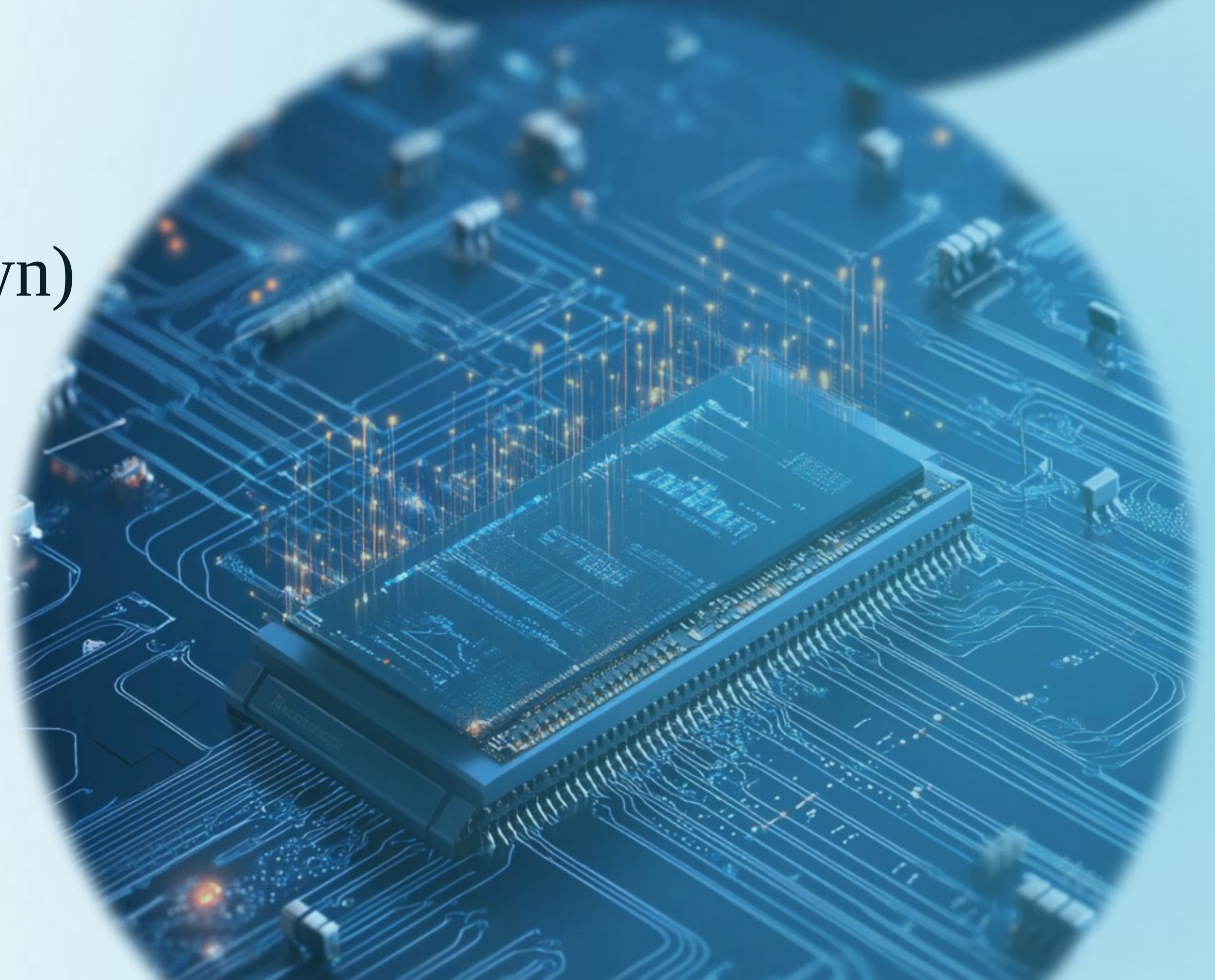
Function:

Converts sound waves to electrical signals using a vibrating diaphragm and capacitive or MEMS technology.

The feature’s extraction :

- Audio features (silence, voice, noise and unknown)
- The power
- Volume of environment audio
- ….





Ambient Light

Definition:

Adjusts screen brightness by measuring surrounding light.

Function:

It uses photodiodes to convert light into electrical signals.

The feature’s extraction :

- The percentage of time the light
- Day and Night
- Sleep duration
- Light intensity
- ….

Proximity

Definition:

Detects nearby objects (e.g., face during calls) to turn off the screen.

.

Function:

It emits infrared waves and measures their reflection to estimate distance

The feature's extraction :

- Detects nearby Bluetooth devices (device proximity)
- the total number of devices that were detected
- ….

Touch screen

Definition:

Detects touch input on the screen for user interaction in mobile phones.

Function:

Uses capacitive technology with a layer of conductive material; when touched, it detects changes in electrical current at the point of contact, translating it into precise input signals.

The feature's extraction :

- Typing Speed
- Screen-on
- Number of screen taps
- …

Camera

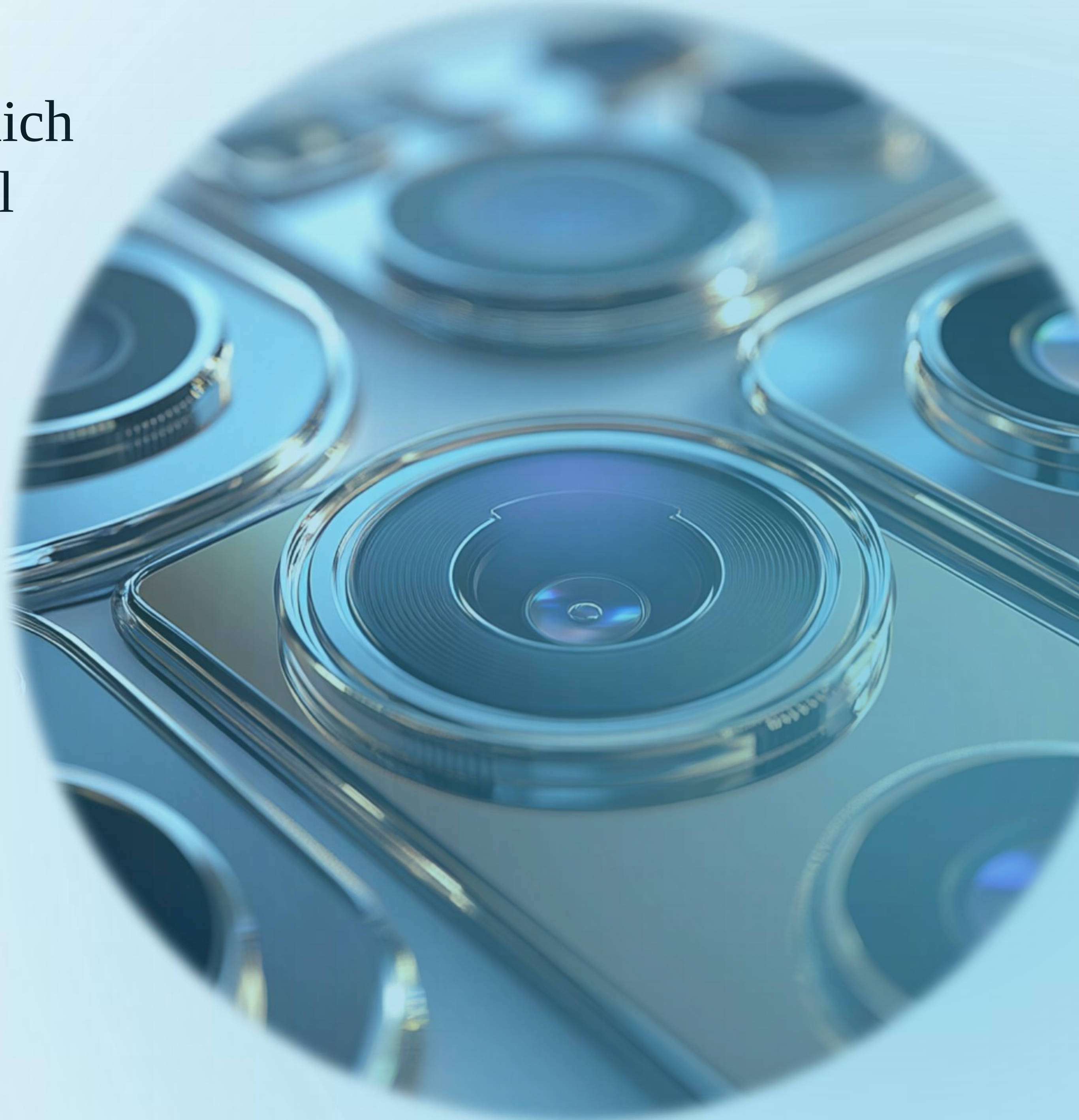
Definition:

Captures images and videos by detecting light in mobile phones.

Function:

Uses a lens to focus light onto a digital sensor, which converts light into electrical signals to form digital images or videos.

The feature’s extraction :



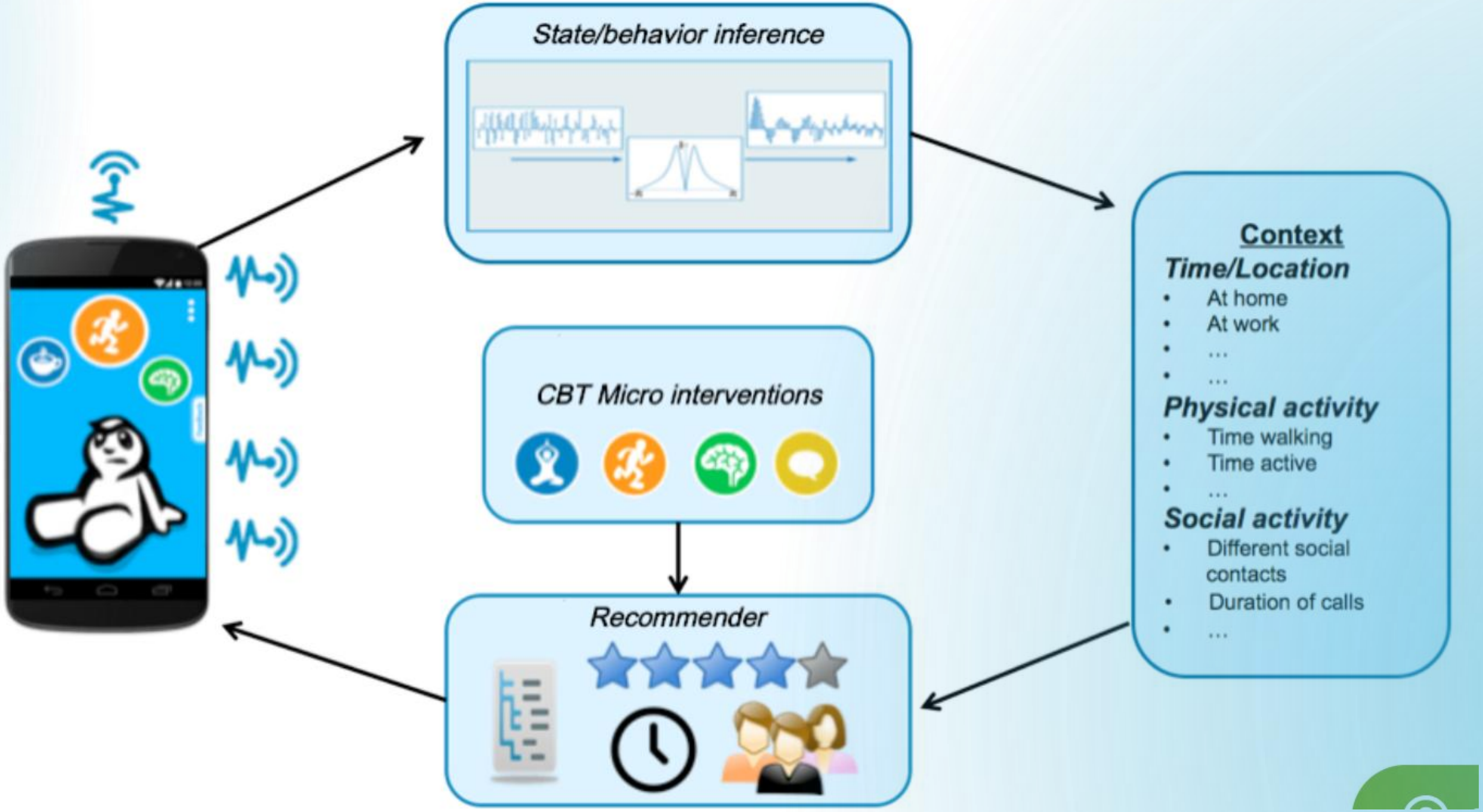
The Relationship Between Mobile Sensing and Depression Monitoring

- Movement patterns
- Voice patterns
- Sleep patterns
- Geolocation
- Light sensors

The Fate of Mobile Sensor Data:

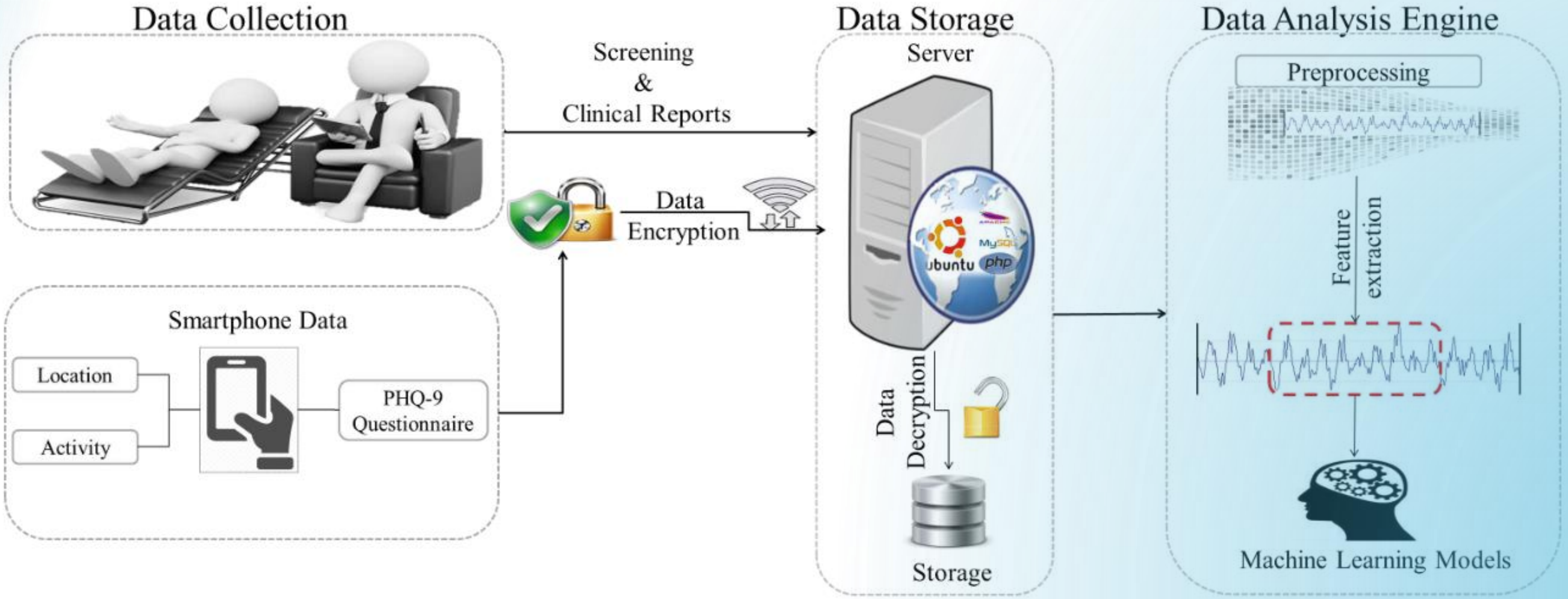
- On-Device Processing
- Server Transmission

On-Device Processing



Mobile Sensing and Support for People With Depression: A Pilot Trial in the Wild
Fabian Wahle

Server Transmission

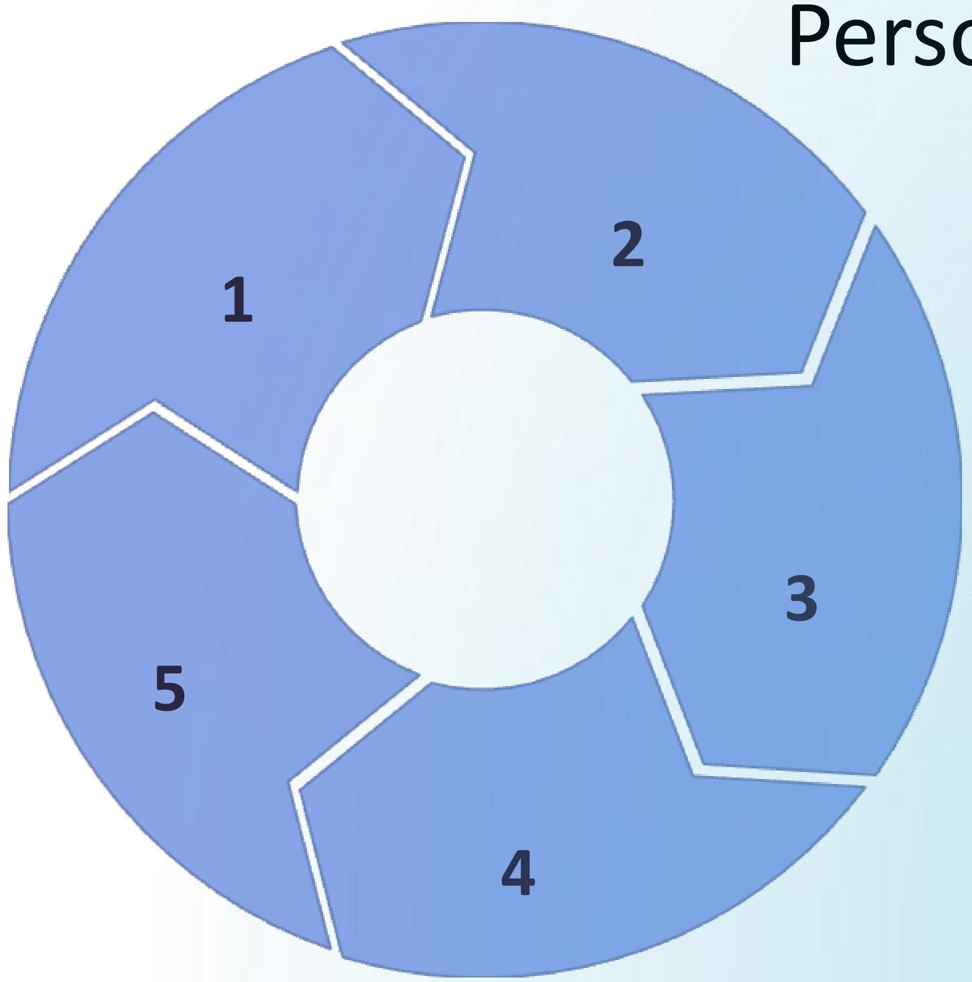


Behavior vs. Introspection: Refining prediction of clinical depression via smartphone sensing data
Asma Ahmad Farhan

An architecture for mobile sensing in the light of telemedicine

Secure Data Transfer

Advantages of Mobile Sensing



Continuous and
real-time Monitoring

Personalized Treatment

Cost Reduction

Scalability

Easy and Widespread
Access

Mobile Sensing Challenges

01 Privacy and Data Security

02 User Consent and Engagement

03 Battery and Resource Consumption

04 Data Accuracy and Quality

05 Device and Model Variability

06 Legal and Regulatory Limitations

07 Environmental and Behavioral Influences

Future of Mobile Sensing

- Increased Accuracy and Number of Sensors
- Artificial Intelligence and Machine Learning
- Integration with Other Smart DevicesHealth
- Monitoring and Disease Prediction
- Enhanced Attention to Privacy
- Greater Accessibility and Lower Cost for All

Conclusion

Understanding Depression

Challenges of Traditional Monitoring Methods

Mobile Sensing as an Innovative Solution

Potential Impact on Mental Health Management

Five relevant articles in this field

01

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Preprints (earlier versions) of this paper are available at https://preprints.jmir.org/preprint/63622, first published June 26, 2024.

Multimodal Digital Phenotyping Study in Patients With Major Depressive Episodes and Healthy Controls (Mobile Monitoring of Mood): Observational Longitudinal Study

Talayeh Aledavood[1]; Nguyen Luong[1]; Ilya Baryshnikov[2, 3]; Richard Darst[4]; Roope Heikkilä[5]; Joel Holmén[6]; Arsi Ikäheimonen[1]; Annasofia Martikkala[2, 3]; Kirsi Riihimäki[3, 7]; Outi Saleva[3]; Ana Maria Triana[1]; Erkki Isometsä[2, 3]

Citation

Please cite as:

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Multimodal Digital Phenotyping Study in Patients With Major Depressive Episodes and Healthy Controls (Mobile Monitoring of Mood): Observational Longitudinal Study
JMIR Ment Health 2025;12:e63622
doi: 10.2196/63622
PMID: 39984168
PMCID: 11890149

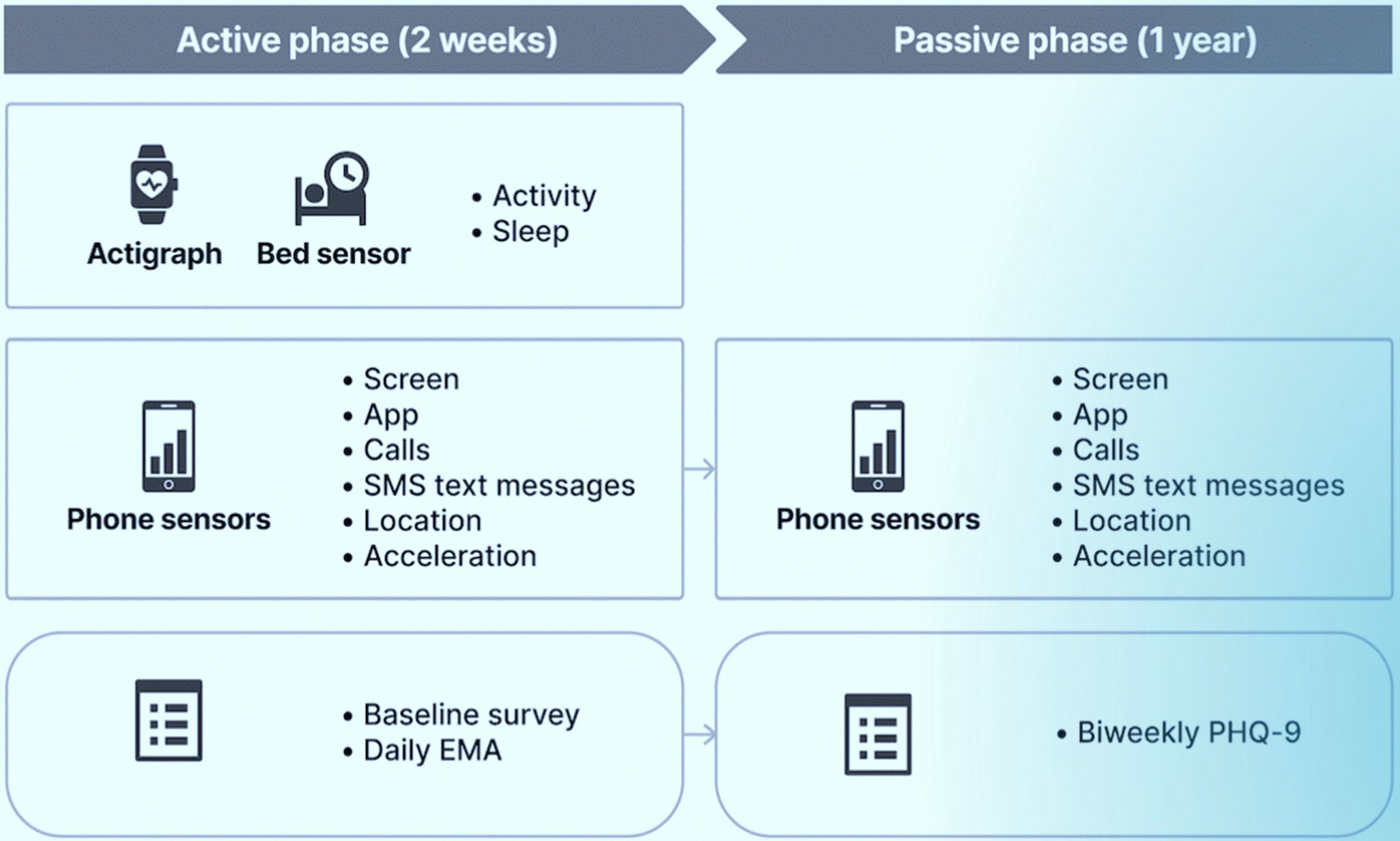
Aims and details

- Examining group differences in spatial, social, smartphone usage, sleep, and physical activity patterns.
- Identifying variables associated with depression severity (based on the PHQ-9 questionnaire).
- Assessing the consistency and homogeneity of behaviors among individuals in the patient group and the healthy group.

- **Participants:**
  - A total of 188 participants, divided into the following groups:
  - **Healthy controls:** 30 participants
  - **Patients with major depressive disorder (MDD):** 76 participants
  - **Patients with bipolar disorder (BD):** 21 participants
  - **Patients with borderline personality disorder (BPD):** 24 participants

- **Study duration:**
  - **Phase 1 (active phase):** 2 weeks
  - **Phase 2 (passive phase):** Up to a maximum of 1 year

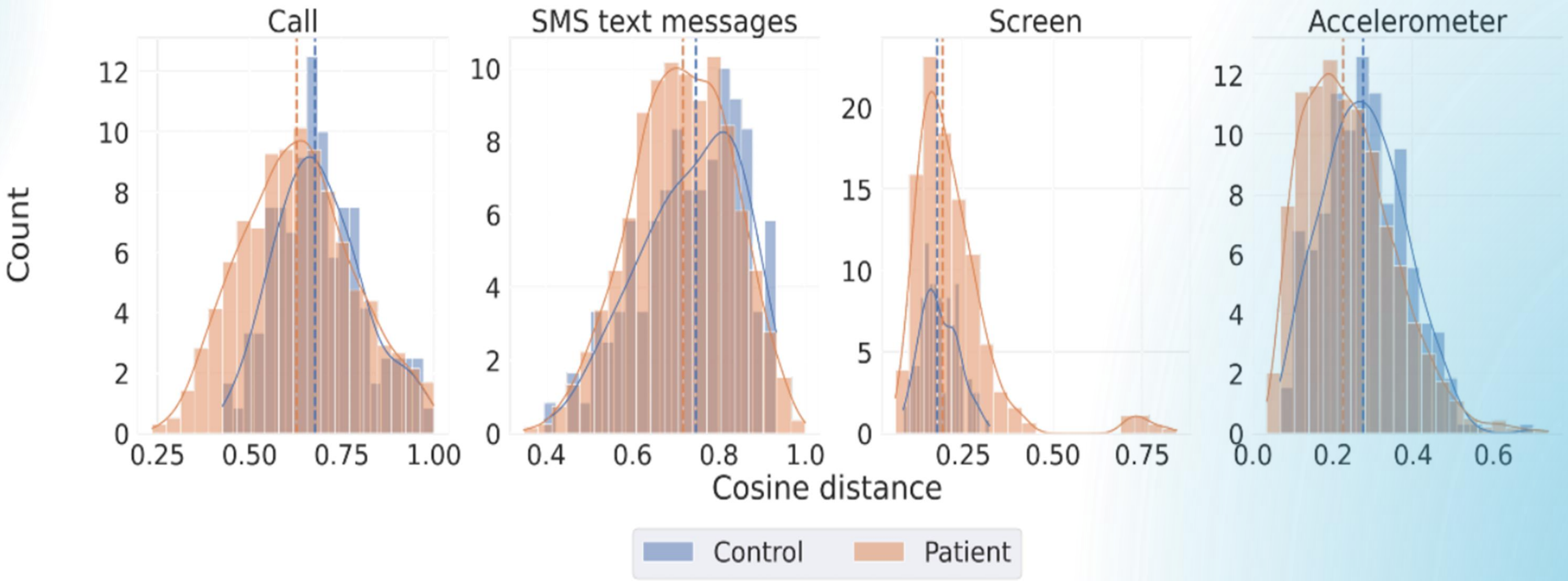
Method:



Active phase (2 weeks)
Passive phase (1 year)
Actigraph
Bed sensor
• Activity
• Sleep
Phone sensors
• Screen
• App
• Calls
• SMS text messages
• Location
• Acceleration
Phone sensors
• Screen
• App
• Calls
• SMS text messages
• Location
• Acceleration
• Baseline survey
• Daily EMA
• Biweekly PHQ-9

Results

Figure 9. Histogram representing the intradifference of weekly rhythm measured by cosine distance. Smaller distances indicate more intraindividual similarity.

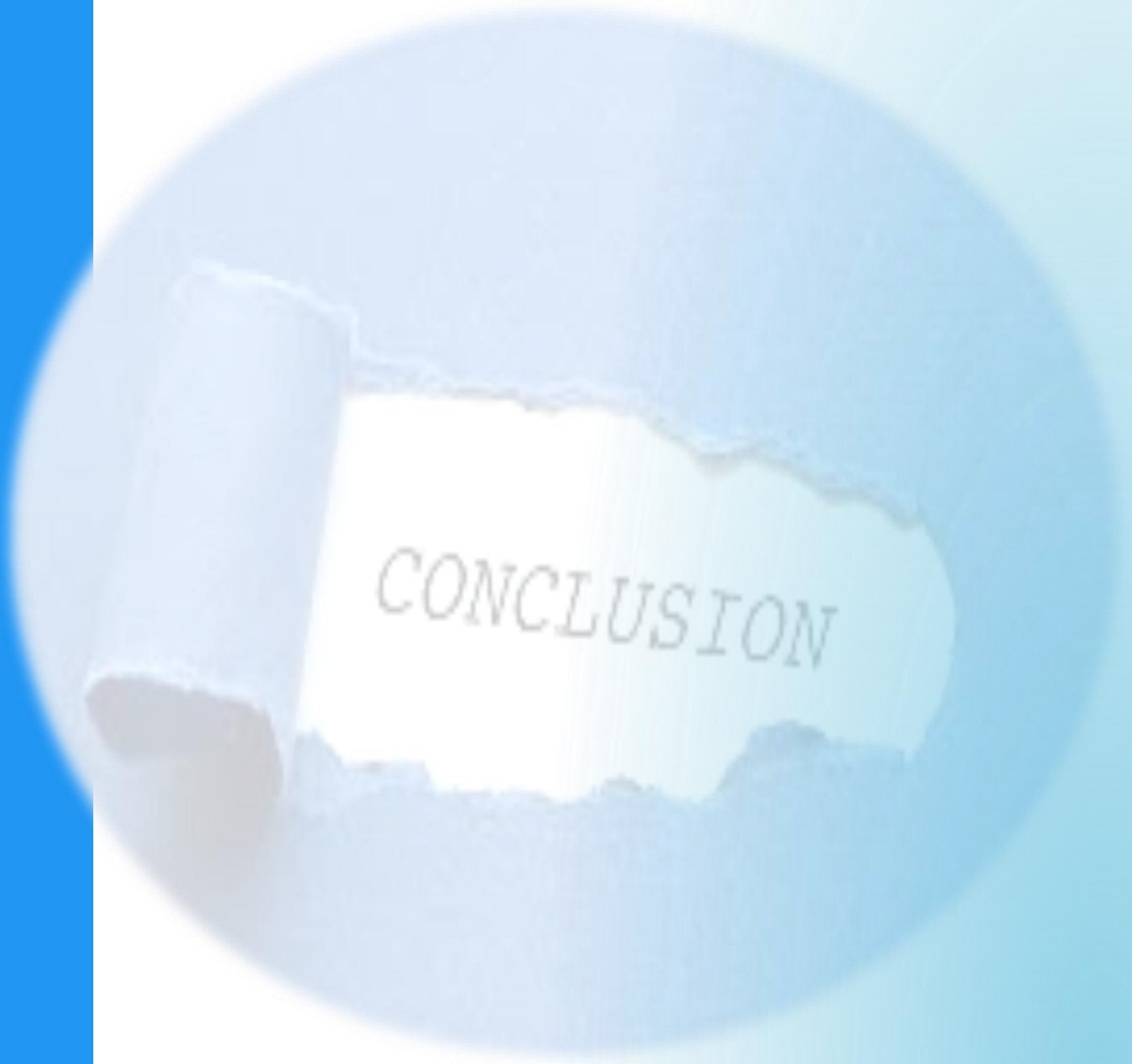


Patients with depression exhibited different behavioral patterns compared to the control group:

- Reduced spatial diversity (lower spatial entropy).
- Increased smartphone usage.
- Decreased incoming communication (calls and messages).

The duration of incoming calls had a negative relationship with depression severity, while the duration of outgoing calls had a positive relationship with depression.

Conclusion of Mobile Monitoring of Mood (MoMo-Mood) Study



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Investigating Smartphone-Based Sensing Features for Depression Severity Prediction: Observation Study

Yannik Terhorst[1, 2, 3]; Eva-Maria Messner[1]; Kennedy Opoku Asare[4]; Christian Montag[5]; Christopher Kannen[5]; Harald Baumeister[1]

Citation

Please cite as:

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Investigating Smartphone-Based Sensing Features for Depression Severity Prediction: Observation Study
J Med Internet Res 2025;27:e55308
doi: 10.2196/55308
PMID: 39883512
PMCID: 11826944

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Exploratory Observational Study

INSIGHTS

Aims and details

The aim: to investigate various features based on the smartphone screen, app usage, and call sensor alongside EMA to infer depression severity.

Number of participants: 368 individuals

Duration of analyzed follow-up: Only a single 14-day (two-week) period per individual

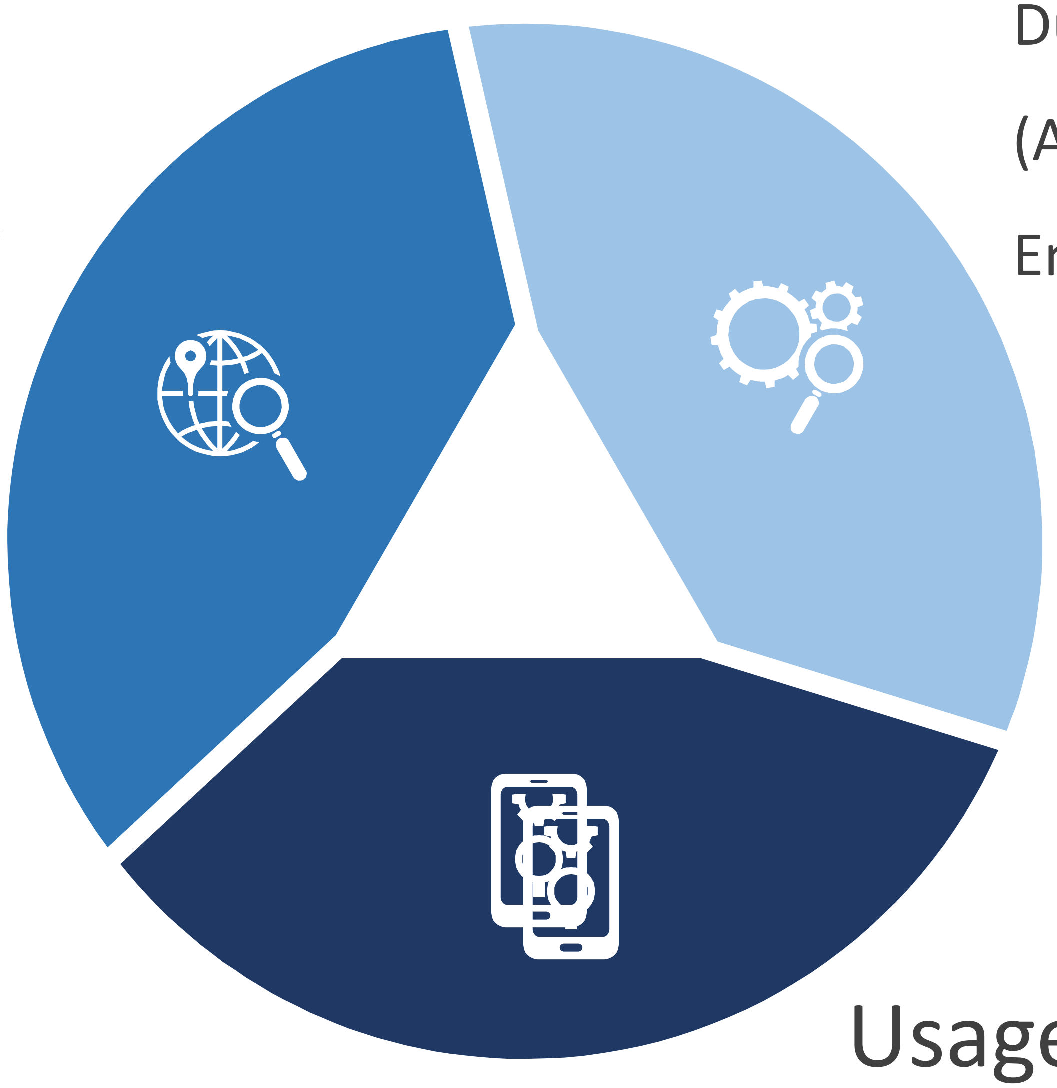
To examine the ability of smartphone sensor data and Ecological Momentary Assessment (EMA) to predict depression severity.

EMA, PHQ-9, sensors

Sensors and features

GPS

- Total Distance Traveled
- Location Variance
- Moving to Static Ratio
- Number of Significant Clusters
- Duration in Clusters
- Location Entropy
- Normalized Location Entropy
- Location Circadian Movement
- Number of Location Transitions
- Proportion of Time in Non-significant Locations (compared to total time)



Call log

Number of Incoming/Outgoing/Missed Calls

Number of Unique Contacts in Incoming/Outgoing Calls

Duration of Incoming/Outgoing Calls (Average, Total, Maximum)

Entropy of Incoming/Outgoing Calls

Usage

Number of Screen Unlocks

Screen Usage Duration

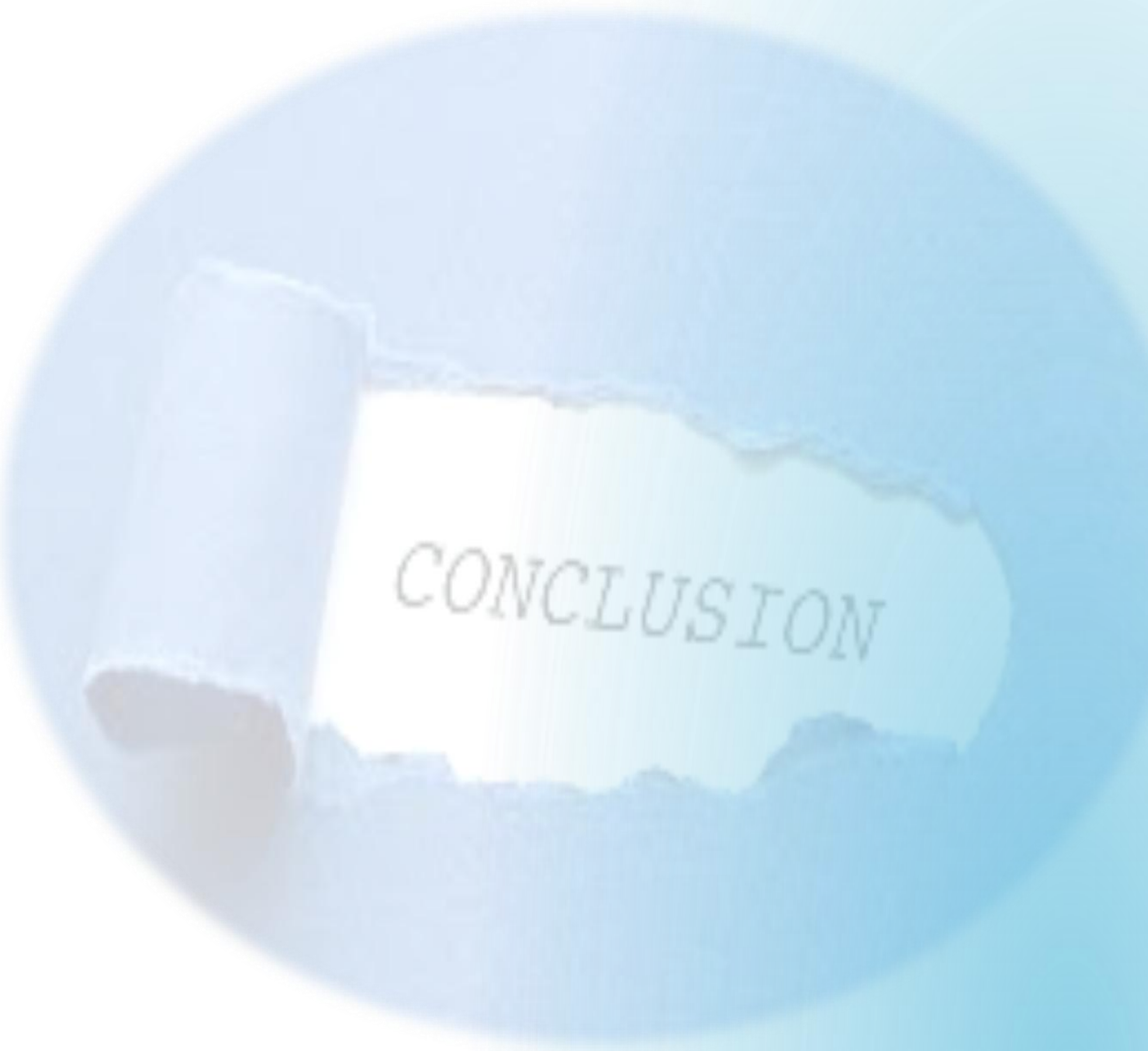
Temporal Regularity Features (Entropy and Regularity): Daily usage patterns

App-related Features

Results

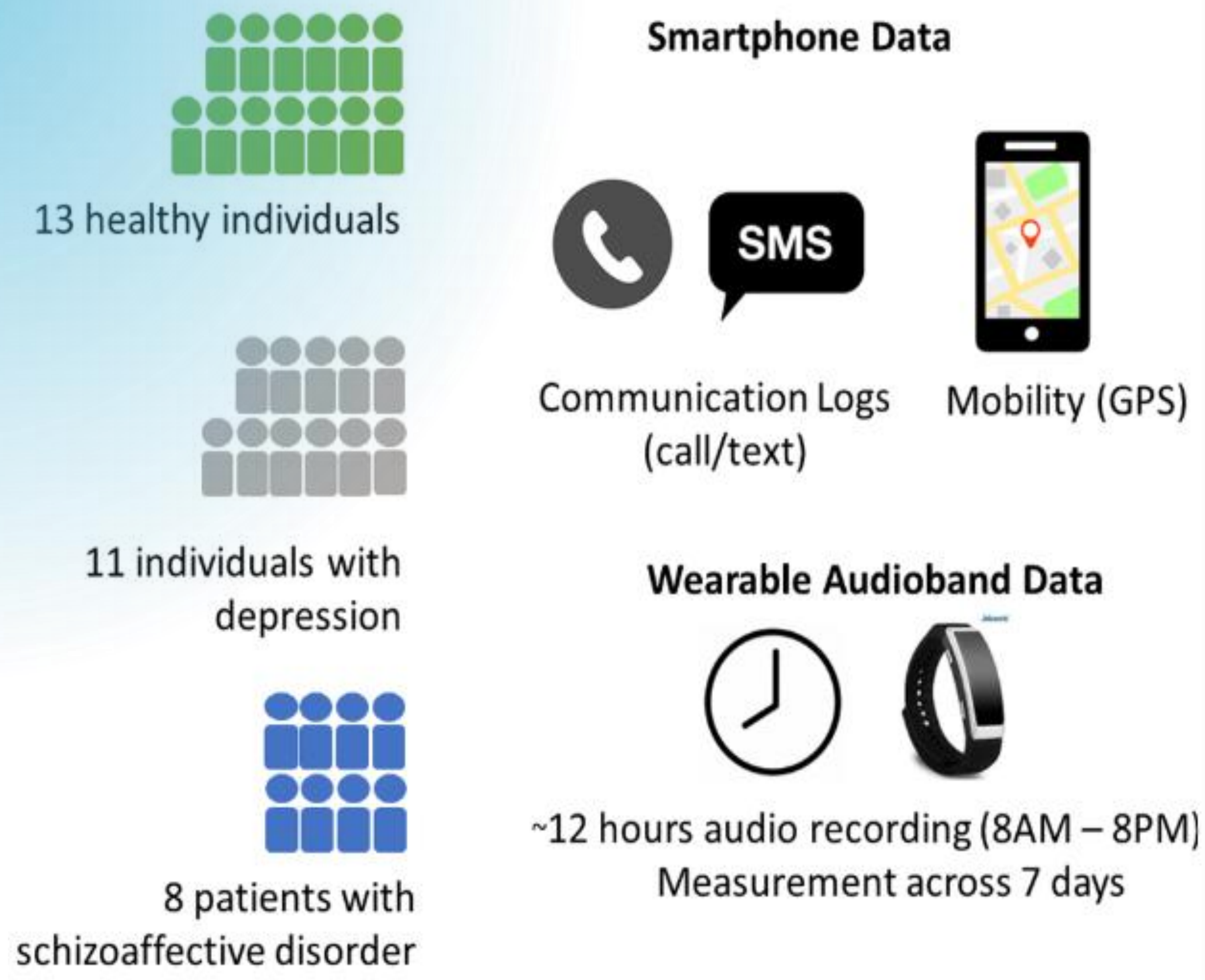
- Daily self-reports (EMA)
- Smartphone sensor data
- Combining these two types of data

Predicting Depression Severity Using EMA and Smartphone Sensor Data



Aim: creating and testing a mobile app-based model that uses sensor data and audio features to measure the severity of depression.

Methods



Communications: Number of calls/SMS, social network, difference between incoming and outgoing calls/SMS

Localization: Mobility, diversity and spatial dispersion

Audio Features: Number and type of face-to-face conversations, size of conversation network

Building three predictive models:

- Communication & localization logs only (Model A)
- Audio features only (Model B)
- Combination of all features (Model C)

Model validation: Leave-One-Participant-Out (LOPO) method
Performance evaluation: Comparison of model accuracies using metrics such as RMSE and F1 Score

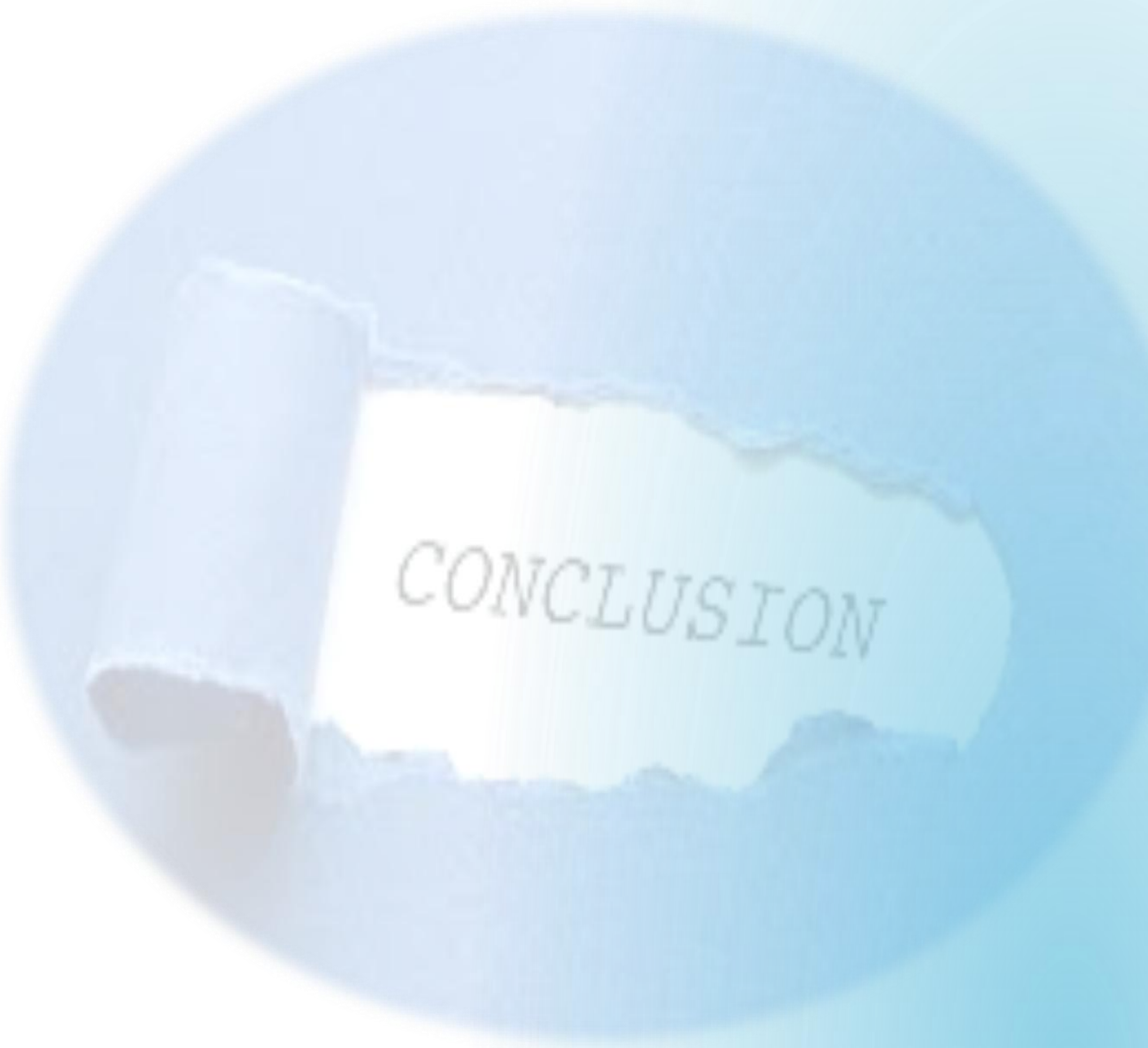
Results

- **Correlation of Depression with Behavioral Features:**

- **Conversation Network Size:** Individuals with higher depression severity had fewer people (face-to-face conversations) in their daily social network.
- **Call and SMS Patterns:** Individuals with greater depression severity made more outgoing messages and calls compared to incoming ones (a “proactive” pattern).
- **Location Information:** Reduced location diversity (Entropy) was associated with higher depression severity.

Model C achieved the best accuracy (F1 = 0.77) in predicting the presence or absence of depression (binary classification).

Predicting Depression Severity Using Mobile & Wearable Sensor Data



RESEARCH-ARTICLE

FacePsy: An Open-Source Affective Mobile Sensing System - Analyzing Facial Behavior and Head Gesture for Depression Detection in Naturalistic Settings

Authors: Rahul Islam, Sang Won Bae | Authors Info & Claims

Proceedings of the ACM on Human-Computer Interaction, Volume 8, Issue MHCI • Article No.: 260, Pages 1 - 32
https://doi.org/10.1145/3676505

Published: 24 September 2024 Publication History

Check for updates

Aim of study:

present and evaluate an open-source mobile system (FacePsy) that detects and monitors depression in real-world situations by analyzing facial behavior and head movements in real-time.

Fig. 2. Examples of Test Images That Succeeds to Capture Features

Study details

Number of participant=25

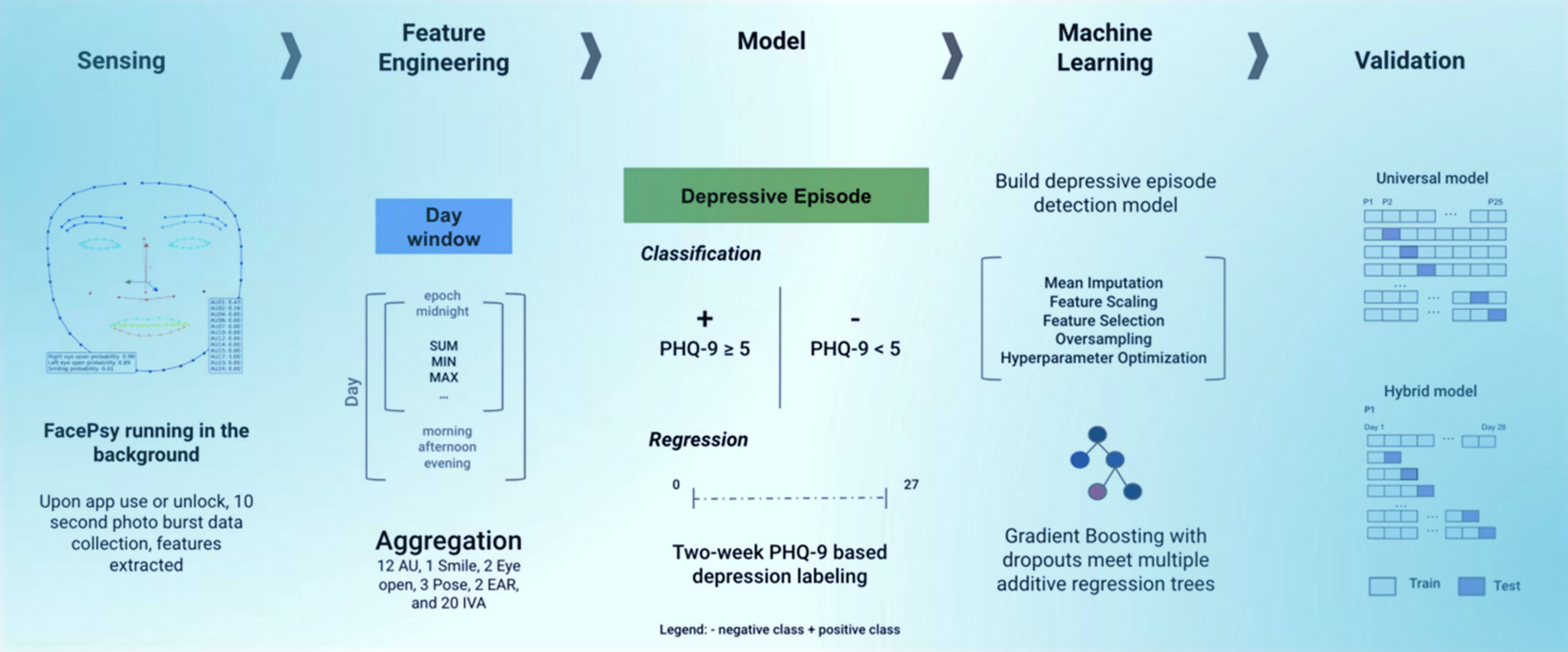
Time of study: 4 weeks

Sensor: camera

Features:

- **Smile probability**
- **Action Units=12**
- **Left/Right Eye-Open Probability**
- **Facial landmarks: 133**

Overview of Affective Mobile System



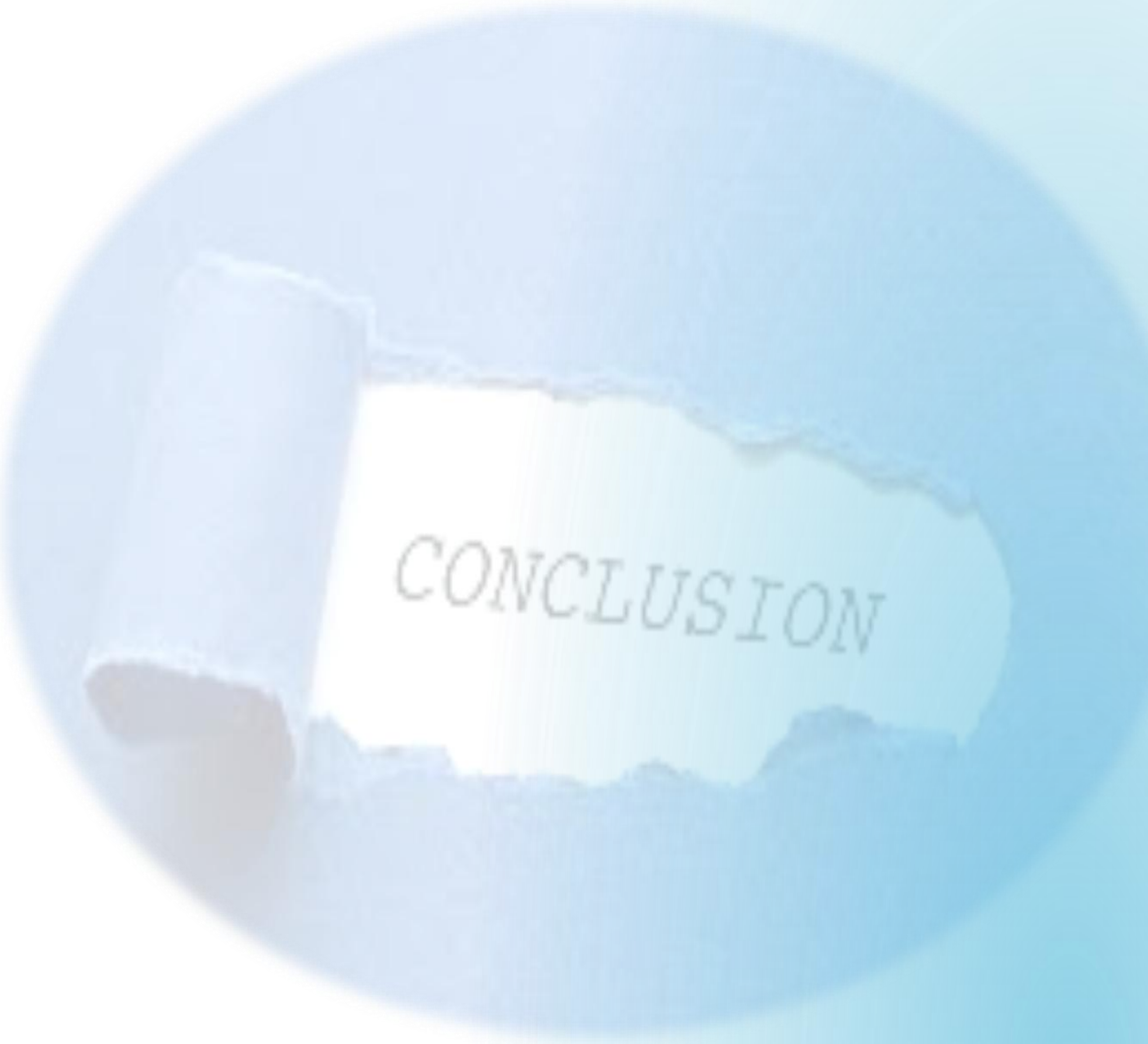
Results

Facial behavioral features (Action Units, smile, eye openness, head pose) were effective in indicating depressive episodes and were unbiased by demographics such as gender or age.

The machine learning model achieved strong performance, distinguishing depressed from non-depressed participants with an AUROC of 81%, and predicted depression severity (PHQ-9 score) with a mean absolute error (MAE) of 3.08.

All feature extraction and processing were performed on-device for privacy, and the system operated efficiently without disrupting smartphone use, enabling real-world, real-time monitoring.

Conclusion of the FacePsy Study



Published on 26.10.2021 in Vol 9, No 10 (2021): October

Preprints (earlier versions) of this paper are available at https://preprints.jmir.org/preprint/20638, first published May 27, 2020.

A Mobile Sensing App to Monitor Youth Mental Health: Observational Pilot Study

Lucy MacLeod[1]; Banuchitra Suruliraj[2]; Dominik Gall[3]; Kitti Bessenyei[1]; Sara Hamm[1]; Isaac Romkey[1]; Alexa Bagnell[1]; Manuel Mattheisen[1]; Viswanath Muthukumaraswamy[1]; Rita Orji[2]; Sandra Meier[1]

Article | **Authors** | **Cited by (19)** | **Tweetations (5)** | **Metrics**

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Please cite as:

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JMIR Mhealth Uhealth
2021;9(10):e20638
doi: 10.2196/20638
PMID: 34698650
PMCID: 8579216

Methods

- The relationship between smartphone sensor data and psychological symptoms was examined.
- Predictive models were developed to assess the impact of integrating sensor data into the estimation of symptoms.

call

Social interactions:

- incoming and outgoing calls
- call duration

GPS

Mobility:

- sitting time
- movement time
- distance traveled
- movement complexity

screen

Phone usage:

- screen time
- the number of times the phone is unlocked.

light

Sleep quality:

- ambient light intensity at night.

- The relationship between smartphone sensor data and psychological symptoms was examined.

- Predictive models were developed to assess the impact of integrating sensor data into the estimation of symptoms.

Results

❑ **Connections:**

✓ Reduced mobility, decreased social interactions, and higher ambient light intensity at night (indicative of poor sleep quality) were associated with depression.

✓ Increased mobility, decreased social interactions, and higher screen usage were associated with anxiety.

❑ **Predictive Models:**

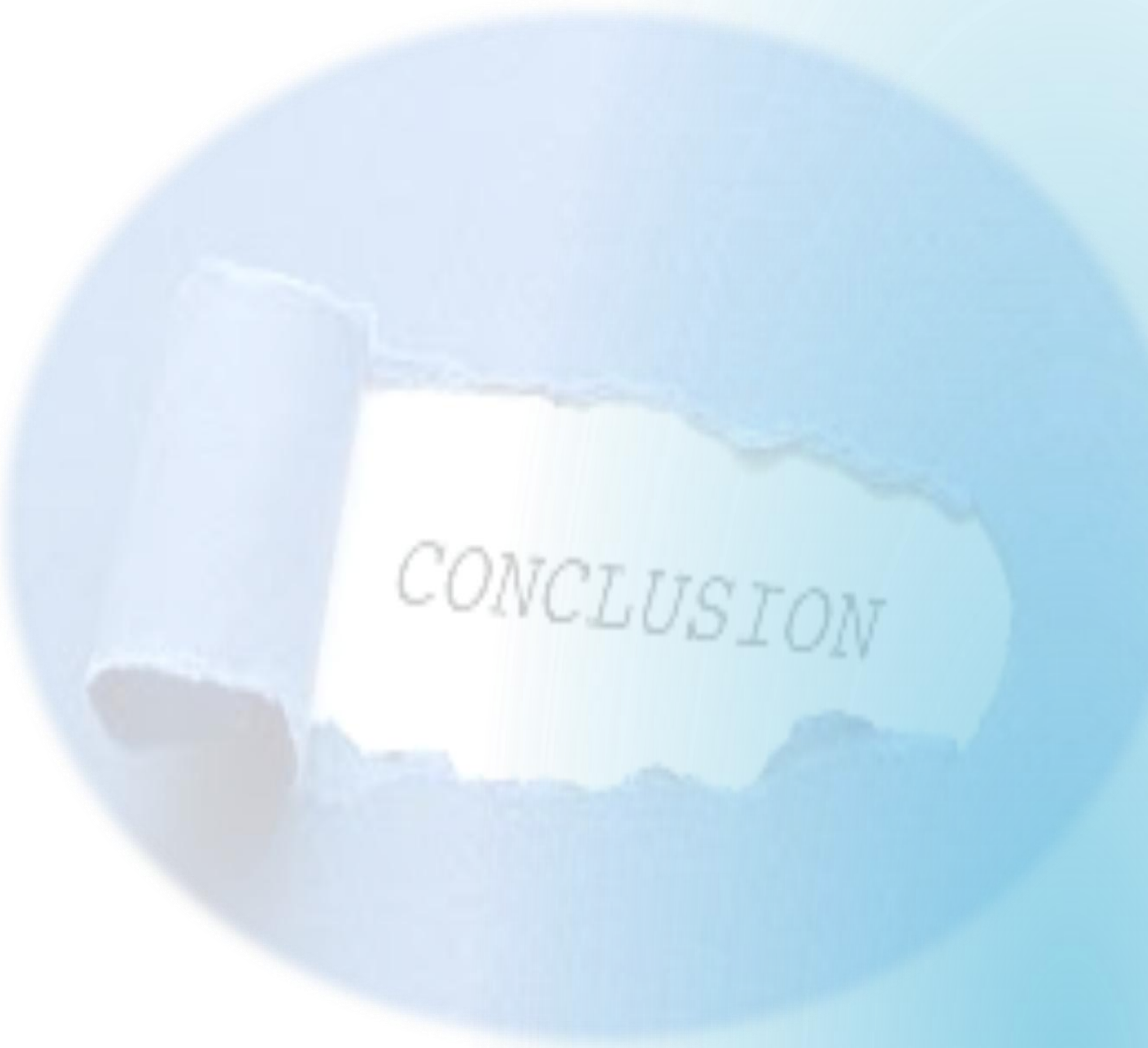
✓ Integrating smartphone sensor data into the models improved the predictive accuracy for symptoms of depression and anxiety.

❑ **Finally:**

✓ Smartphone sensor data can be used to predict internal psychological symptoms (anxiety and depression) in young people.

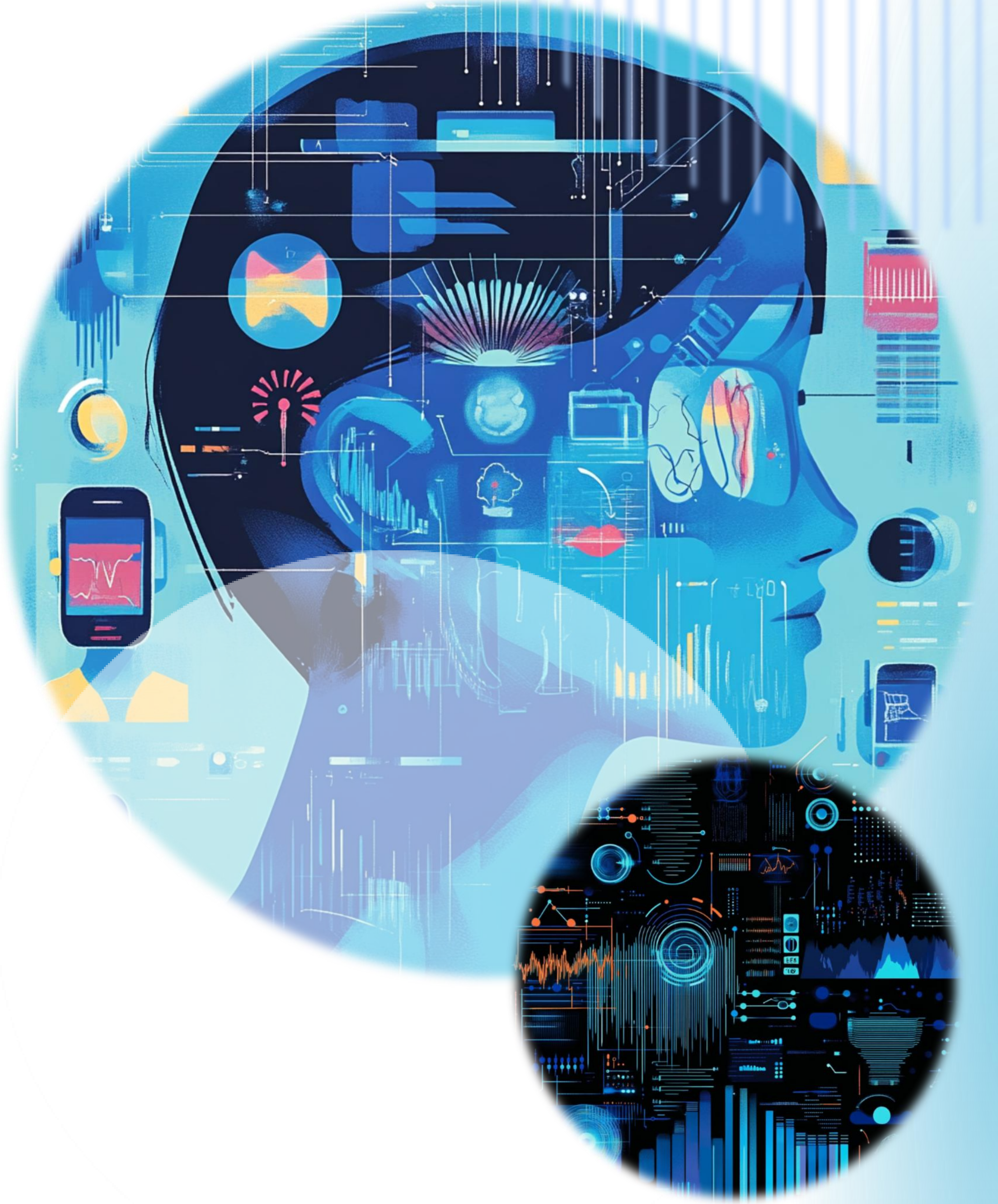
✓ These data have the potential for early identification of symptoms but cannot determine the exact cause of psychological issues.

Conclusions of Smartphone Data for Predicting Youth Mental Health Symptoms



Final Conclusion

- **Innovative Tool**: Mobile Sensing uses smart device sensors for non-invasive, cost-effective
- **Transformative Impact**: With EMA and FacePsy, it can revolutionize mental health management and support clinical decisions.
- **Ethical Focus**: Privacy and security of sensitive health data, especially for youth, are critical.
- **Balanced Use**: Must balance technological benefits with ethical concerns for safe adoption.



Thank you for your attention