Data Collection with Wearables, Apps, and Sensors

#WAPOR WEBINAR SERIES 2023

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What I will talk about

- Why use wearables, apps, & sensors for data collection
- What we can measure with wearables, apps, & sensors
- What challenges are there when using wearables, apps, and sensors for data collection

Acknowledgement

The materials presented here are the result of various research collaborations and joint teaching with:

Sebastian Bähr, Frederick Conrad, Mick Couper, Stephanie Eckman, Heidi Guyer, Georg-Christoph Haas, Frauke Kreuter, Peter Lugtig, Bella Struminskaya, Mark Trappmann, and many more…

Why use wearables, apps, & sensors for data collection

Potential benefits of wearables, apps, & sensors

1. Taking advantage of technology that is widely used in society
    - High smartphone penetration & quantified-self movement
    - Device present in same physical and social context as user
    - Moving from small scale lab studies to larger scale field studies

Potential benefits of wearables, apps, & sensors

1. Taking advantage of technology that is widely used in society
2. Multiple (new) forms of measurement on a single device
   - *In situ* measurement (e.g., EMA/ESM)
   - *Passive measurement* with sensors (e.g., automatic collection of location and activity)
   - Use of other device features for *active measurement* (e.g., photos, videos)
   - Smartphone as *hub* for other devices (e.g., smart watch, smart scale, via Bluetooth)

Potential benefits of wearables, apps, & sensors

1. Taking advantage of technology that is widely used in society
2. Multiple (new) forms of measurement on a single device
3. More detailed data (frequency and intensity)
   - High frequency of measurement (e.g., intensive longitudinal measurement, passive measurement)
   - Much more fine-grained data than in traditional longitudinal designs
   - New types of information that cannot be self-reported (e.g., different stages of sleep)

Potential benefits of wearables, apps, & sensors

1. Taking advantage of technology that is widely used in society
2. Multiple (new) forms of measurement on a single device
3. More detailed data (frequency and intensity)
4. Unobtrusive, direct measurement should lead to more accurate estimates
    - Less self-report = Less recall error
    - Less self-report = (Potentially) less social desirability
    - Less self-report = Less data entry error

Potential benefits of wearables, apps, & sensors

1. Taking advantage of technology that is widely used in society
2. Multiple (new) forms of measurement on a single device
3. More detailed data (frequency and intensity)
4. Unobtrusive, direct measurement should lead to more accurate estimates
5. Less response burden
   - Fewer survey questions have to be asked about (Harari et al. 2017)…
     - Smartphone-mediated behaviors (e.g., # of calls & text messages, Internet browsing, app use)
     - Non-mediated behaviors (e.g., physical activity, sleep, movement, travel)
     - Daily activities (e.g., food intake, expenditure)
   - But what about other burden? - Consent, compliance, privacy, etc.

Potential benefits of wearables, apps, & sensors

1. Taking advantage of technology that is widely used in society
2. Multiple (new) forms of measurement on a single device
3. More detailed data (frequency and intensity)
4. Unobtrusive, direct measurement should lead to more accurate estimates
5. Less response burden
6. Collecting data at scale
   - ~22,000 volunteer iPhone users downloaded *Mappiness* app and shared activities and affect (EMAs) plus geolocation (GPS) for 6 months (MacKerron & Mourato 2013)
   - >100,000 participants of the UK Biobank study wore wrist accelerometer for 7 days (Doherty et al. 2017)

Potential benefits of wearables, apps, & sensors

1. Taking advantage of technology that is widely used in society
2. Multiple (new) forms of measurement on a single device
3. More detailed data (frequency and intensity)
4. Unobtrusive, direct measurement should lead to more accurate estimates
5. Less response burden
6. Collecting data at scale
7. New research questions?

What we can measure with wearables, apps, and sensors

Different devices with sensors

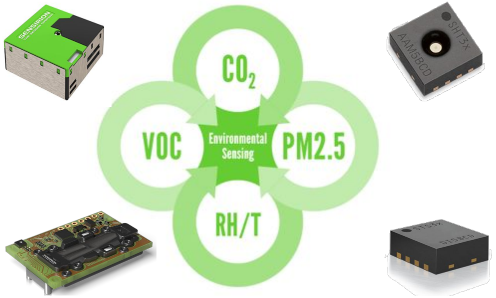
Source:
https://www.youtube.com/watch?v=FEr9D2glDXA

Source: https://www.techradar.com/news/wearables/10-best-fitness-trackers-1277905

Sources:
http://www.canadagps.com/CanmoreGT-750FL_Sirf4.html
https://www.laserinst.com/trimble-geo7x-handheld/

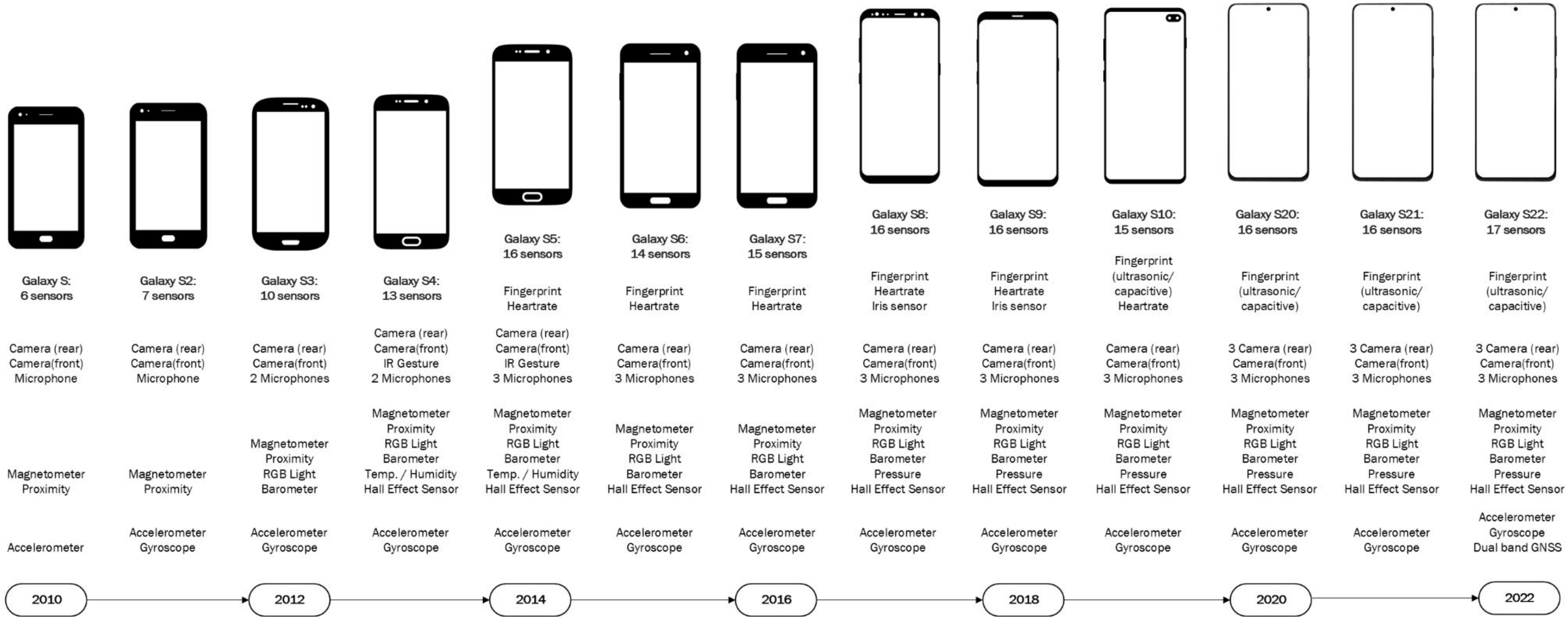
Source: https://www.techradar.com/news/wearables/best-smart-watches-what-s-the-best-wearable-tech-for-you-1154074

Sources:
https://www.actigraphcorp.com/actigraph-wgt3x-bt/,
https://www.activinsights.com/products/geneactiv/



Source:
https://www.sensirion.com/en/environmental-sensors/

Smartphones & sensors



Struminskaya & Keusch. (2023)

Native smartphone sensors

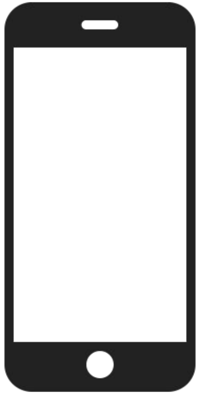
NFC

Heart rate sensor

Bluetooth

Air humidity sensor

Thermometer



Proximity sensor

Wi-Fi

Microphone

GPS

Cellular network

Light sensor

Fingerprint sensor

Camera

Barometer

Compass

Accelerometer

Pedometer

Gyroscope

Native smartphone sensors

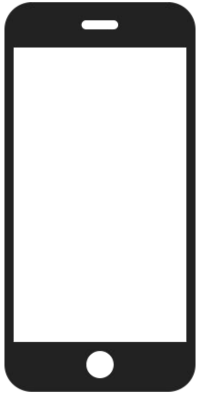
Proximity
NFC
Bluetooth

Heart rate sensor

Air humidity sensor

Thermometer

Location
Wi-Fi
GPS
Cellular network



Proximity sensor

Microphone
Light sensor
Ambience/ Environment

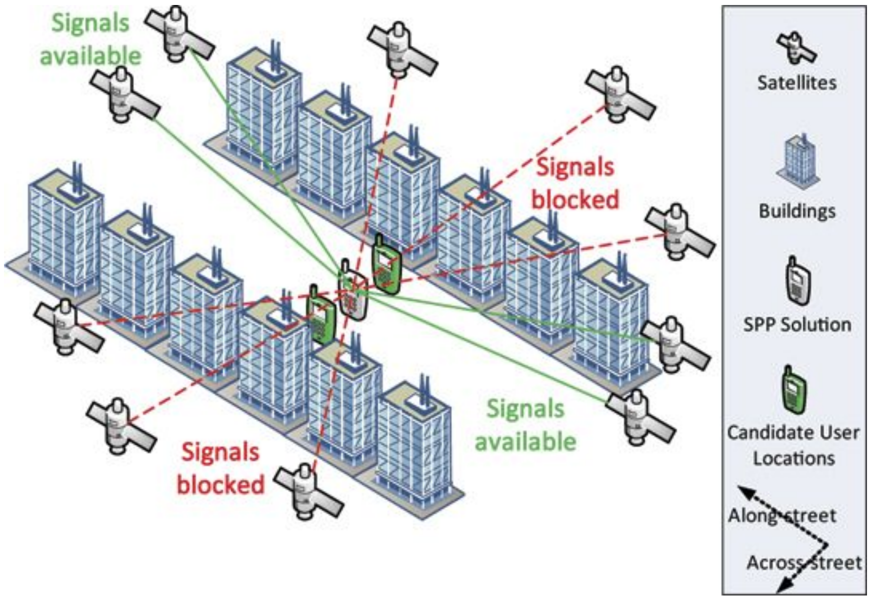
Camera

Fingerprint sensor

Barometer
Compass
Accelerometer
Pedometer
Gyroscope
Physical activity

Geolocation

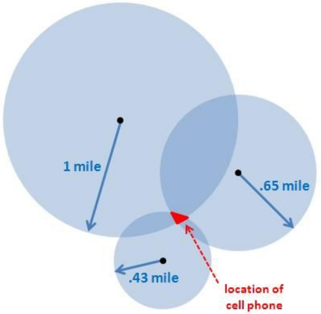
- GPS
  - Provides coordinates in longitude & latitude
  - Based on distance (= rate x time) to at least 4 satellites
  - Newest generation has accuracy within 30 centimeters
  - Works without cell/Internet connection
  - Performs worse in ‘urban canyons’, indoors, & underground
  - Constant tracking is very battery-draining



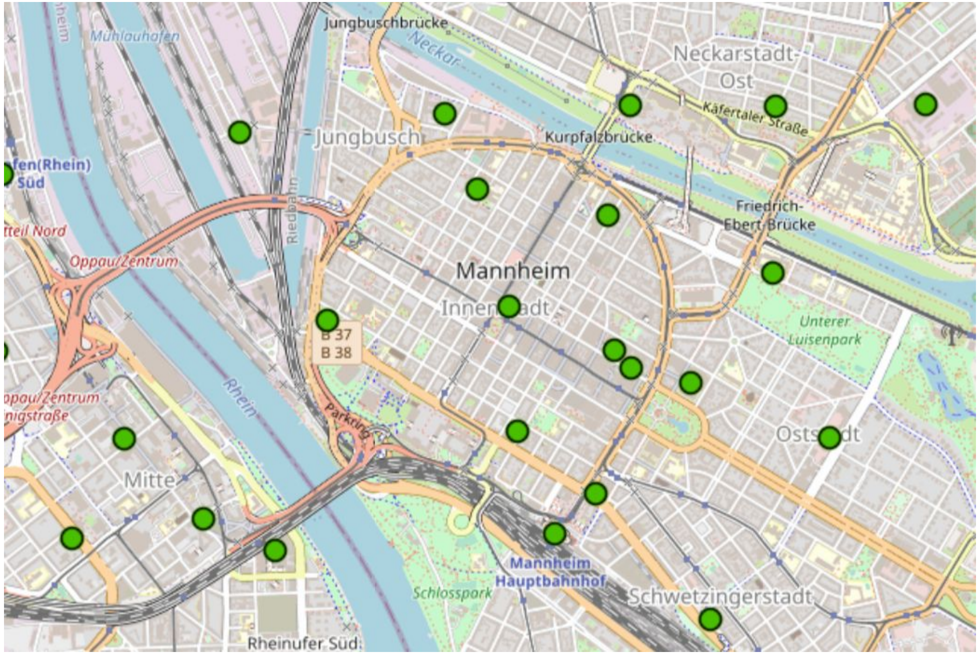
Source: https://www.gpsworld.com/wirelesspersonal-navigationshadow-matching-12550/

Geolocation

- GPS
- Cellular network
  - Multilateration of radio signals between (several) cell towers
  - Works even if GPS is turned off
  - If there is no signal then location information will be missing



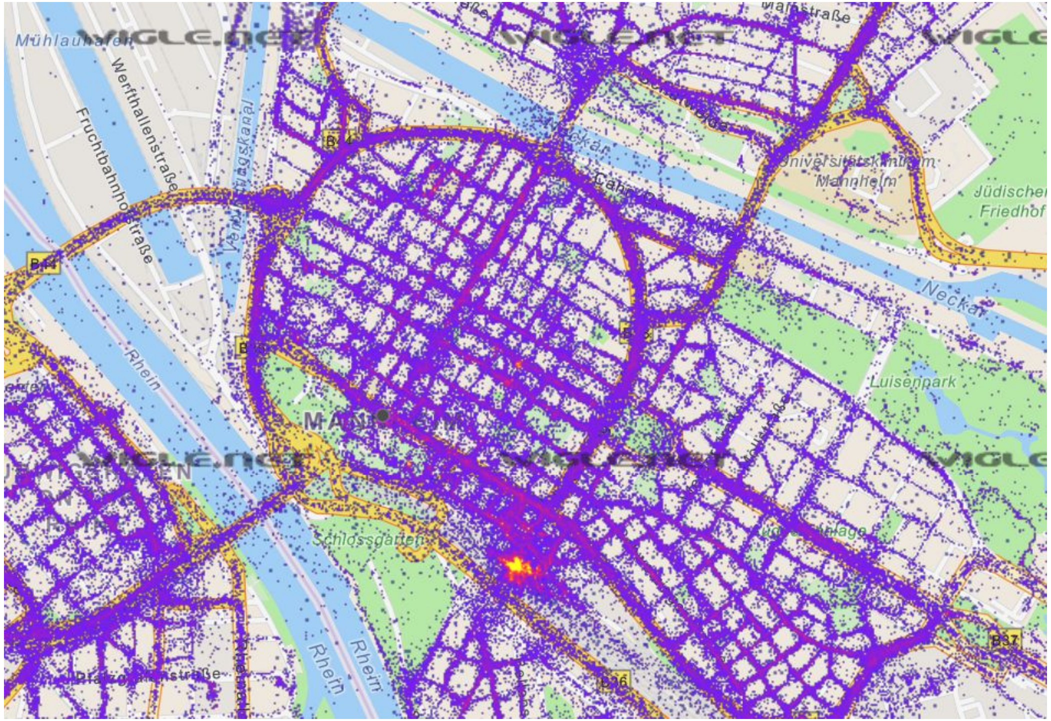
Source: https://searchengineland.com/cell-phone-triangulation-accuracy-is-all-over-the-map-14790



Source: https://www.cellmapper.net

Geolocation

- GPS
- Cellular network
- Wi-Fi
    - Inferring location from Wi-Fi access points (AP)
    - Can overcome problem of ‘urban canyons’ and indoor tracing



Source: https://www.wigle.net

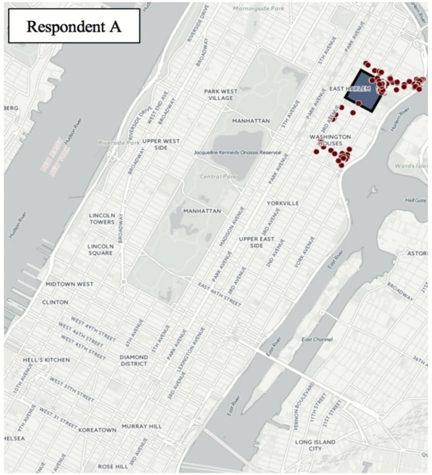
Geolocation

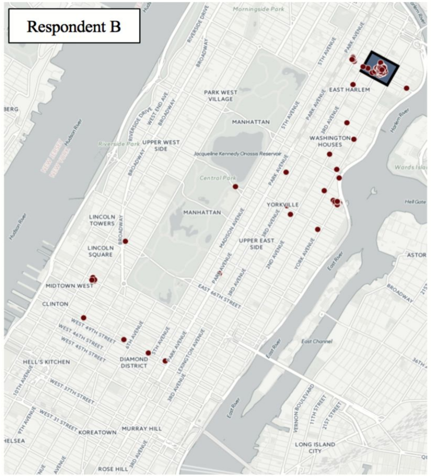
- GPS
- Cellular network
- Wi-Fi
- Hybrid positioning systems
  - Uses combination of systems to make location more accurate (assisted GPS - AGPS)
  - E.g., fall-back on X if Y is not available

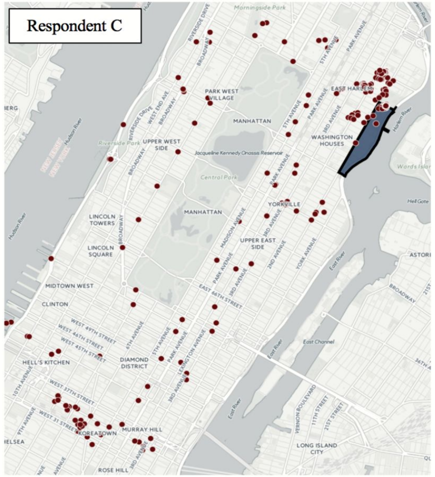
Example: Aging in activity space

(York Cornwell & Cagney 2017, 2020)

- *Real-time Neighborhoods and Social Life Study* (RNSL)
- 60 participants aged 55+ in NYC provided with iPhones to carry for 7 days
- GPS-tracking (every 5 min) from 9 a.m. to 9 p.m and four EMAs per day



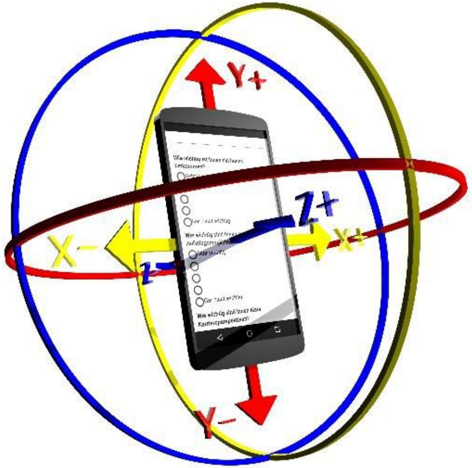


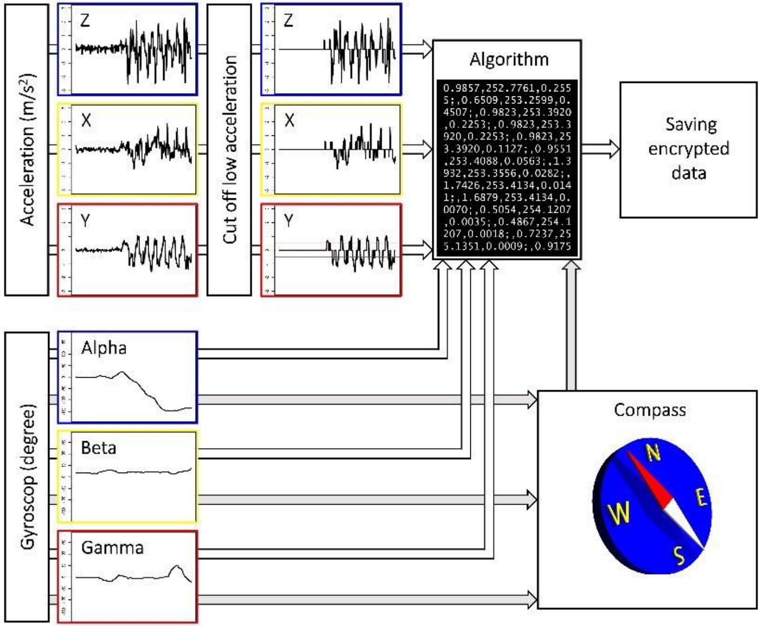


Physical activity

- Accelerometer
- Gyroscope

Source: https://www.techradar.com/news/wearables/10-best-fitness-trackers-1277905





Schlosser et al. (2019)

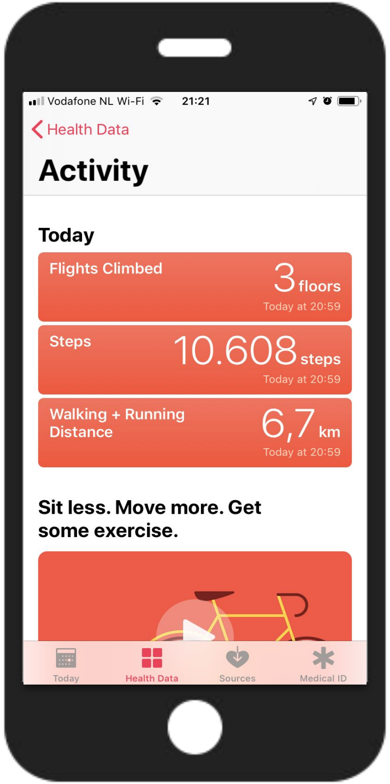
Sources: https://www.actigraphcorp.com/actigraph-wgt3x-bt/, https://www.activinsights.com/products/geneactiv/

Physical activity

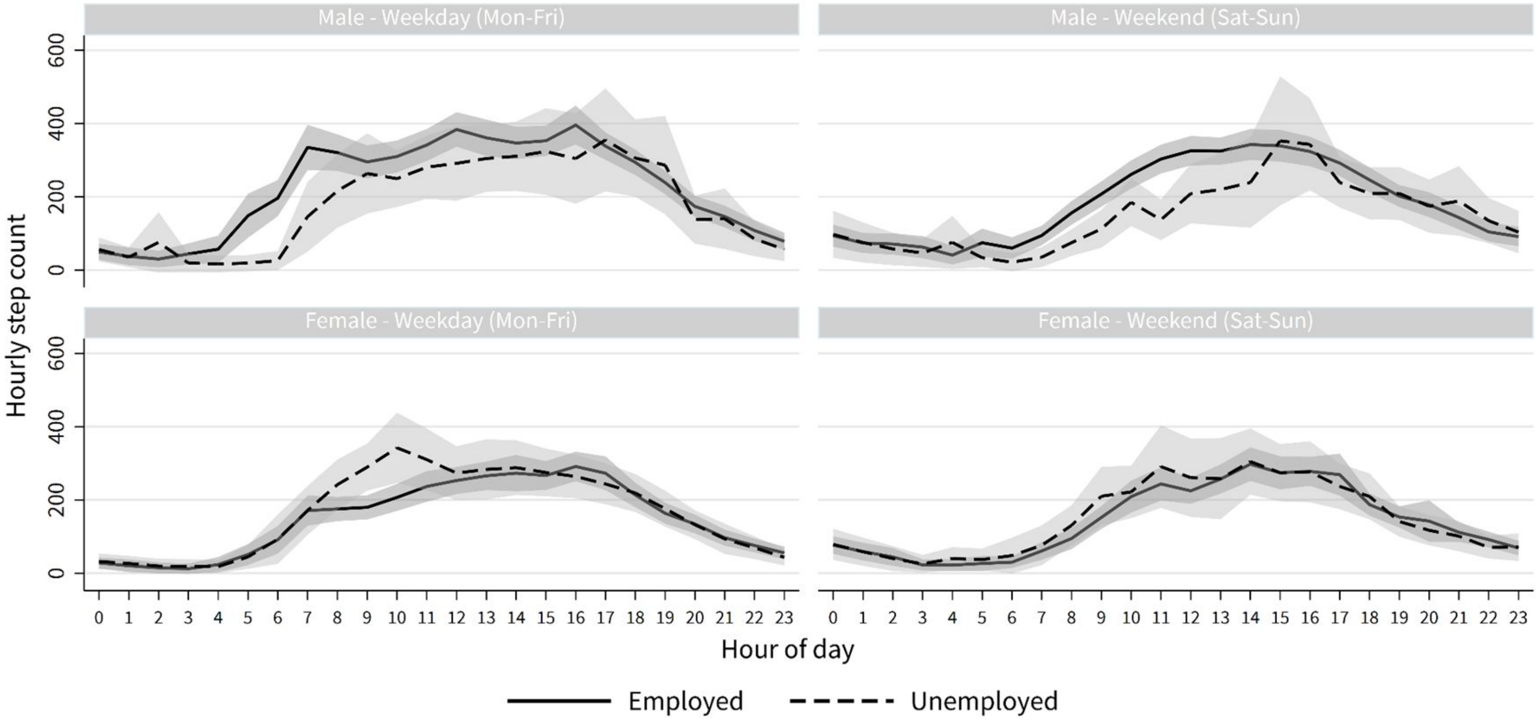
- Accelerometer
- Gyroscope

and

- Magnetometer
  - Serves as compass
- Barometer
  - Allows to track changes in elevation

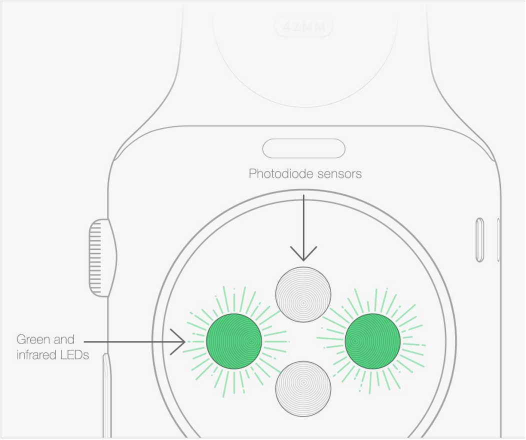


Example: What are the effects of unemployment on physical activity? (Bähr et al. in preparation)

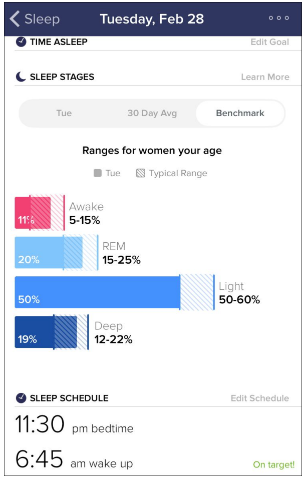


Heart-rate

- Most wristbands use LED-based system
    - Light “shines” onto skin, sensor detects blood volume changes
    - “... finely-tuned algorithms are applied to measure heart rate automatically and continuously…” (https://help.fitbit.com/articles/en_US/Help_article/1565)
    - Samsung Galaxy S uses similar system
- Used in combination with accelerometer to determine sleep phases (e.g., on Fitbit)



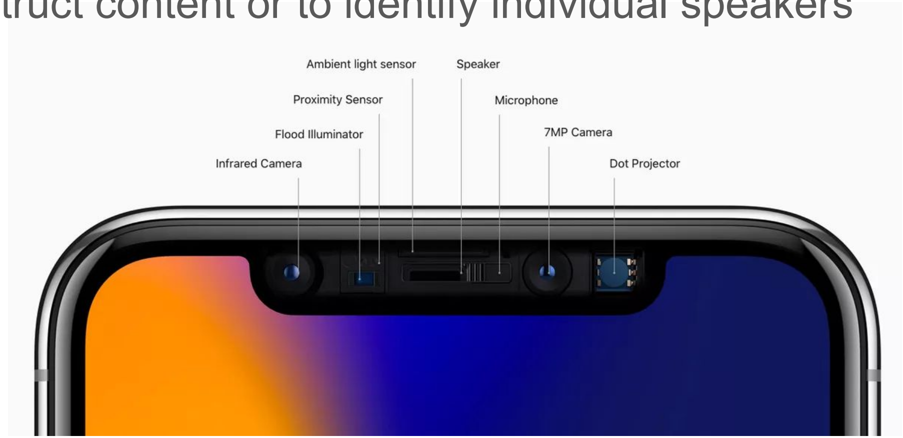
Source: https://exist.io/blog/fitness-trackers-heart-rate/



Source: https://help.fitbit.com/articles/en_US/Help_article/2163

Sound & light

- Microphone
  - “Actively” records answers to survey questions
  - “Passively” measures ambient noise (e.g., clutter), music, and conversations
  - To preserve privacy, classifiers determine that participant is, for example, “around conversation” but not able to reconstruct content or to identify individual speakers
- Light sensor
  - Used to adjust display brightness
  - In combination with other sensors (e.g., accelerometer, microphone) infers idle state of phone/user & sleep



Source: https://www.theverge.com/circuitbreaker/2017/9/15/16307802/apple-iphone-x-features-specs-best-worst

Example: Does mental health of students change over the course of a term?

(Wang et al. 2014)

- Students who sleep less, interact less with other students, have fewer co-locations with others more likely to be depressed
- Students around more conversation and students who move around less while on campus do better academically

Correlation with depression

automatic sensing data	r	p-value
sleep duration (pre)	-0.360	0.025
sleep duration (post)	-0.382	0.020
conversation frequency during day (pre)	-0.403	0.010
conversation frequency during day (post)	-0.387	0.016
conversation frequency during evening (post)	-0.345	0.034
conversation duration during day (post)	-0.328	0.044
number of co-locations (post)	-0.362	0.025

Correlation with academic performance

academic performance	Sensing Data	r	p-value
spring GPA	conversation duration (day)	0.356	0.033
spring GPA	conversation frequency (day)	0.334	0.046
spring GPA	indoor mobility	-0.361	0.031
spring GPA	indoor mobility during (day)	-0.352	0.036
spring GPA	indoor mobility during (night)	-0.359	0.032
overall GPA	activity duration	-0.360	0.030
overall GPA	activity duration std deviation	-0.479	0.004
overall GPA	indoor mobility	-0.413	0.014
overall GPA	indoor mobility during (day)	-0.376	0.026
overall GPA	indoor mobility during (night)	-0.508	0.002
overall GPA	number of co-locations	0.447	0.013

Proximity - Bluetooth

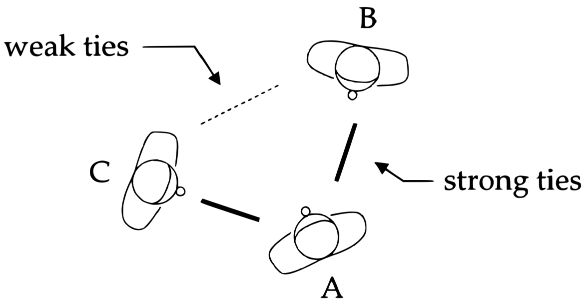
- Short-range communication between devices up to 30 m
  - e.g., hands-free devices, audio speakers, printers
- Enabled healthcare devices can connect to smartphones or other hubs to transmit data
  - e.g., weight, blood pressure, temperature, heart rate, etc.
- Beacons = small Bluetooth transmitters
  - Need to be dispatched by researcher
  - Bluetooth needs to be activated on receiving device
  - Great for indoor tracking

Source: https://www.renesas.com/jp/en/solutions/proposal/bluetooth-low-energy.html

Source: Silvana Jud

Proximity - RFID & NFC

- Radio-frequency identification (RFID): electromagnetic fields to automatically identify and track tags attached to objects ~1 meter (3 feet)
  - e.g., assembly lines, merchandise in warehouses, livestock
- Near-field communication (NFC): communication between devices by bringing them within 4 cm (1.6 in) of each other
  - More secure than RFID
  - e.g., contactless payment, data transfer, key cards
- All of them (incl. Bluetooth) can be used to track "social ties"



Source: https://upload.wikimedia.org/wikipedia/commons/2/2a/Weak-strong-ties.svg

Example: How do people interact in large social networks? (Stopczynski et al. 2014)

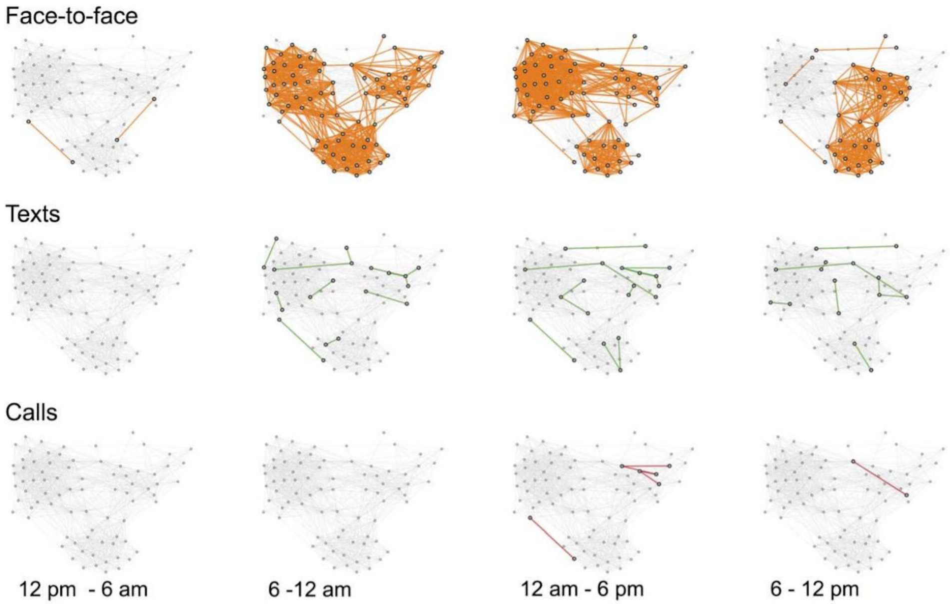


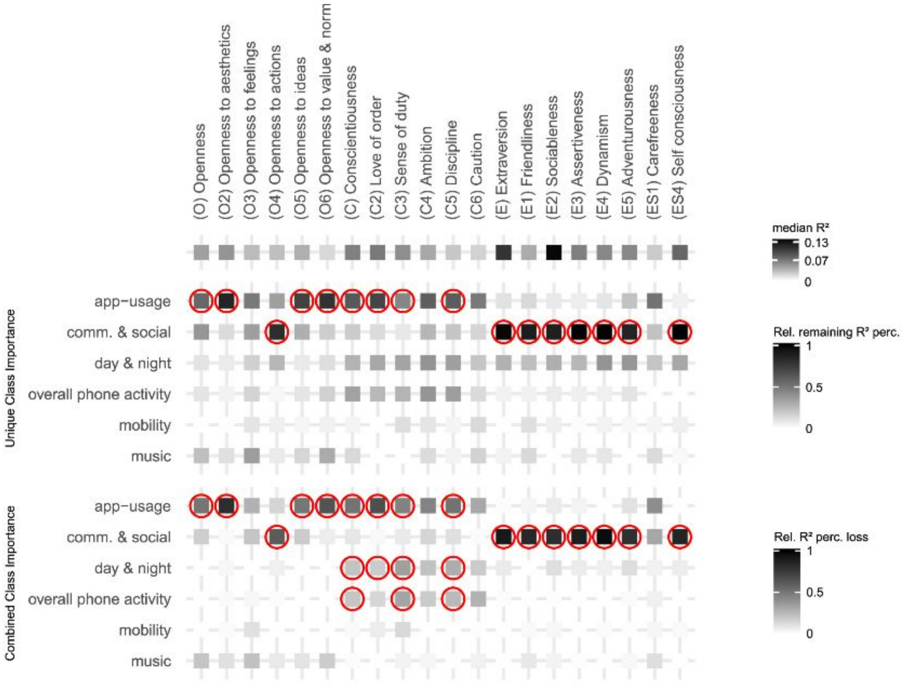
Figure 11. Daily activations in three networks. One day (Friday) in a network showing how different views are produced by observing different channels.

Digital phenotyping

- Activities inherent to functions of smartphone (*smartphone-mediated behaviors*) are captured in use logs of device's OS
  - e.g., phone calls, text messages, app use, Internet browsing behavior, setting changes
  - Logs usually include information about type of activity, time, and duration - NO information about content
- Alternative approaches
  - In-app content measurement (Murmuras)
  - Human Screenome (Reeves et al. 2020)
- What actually can be recorded depends on OS and user settings
  - iOS much more restrictive than Android

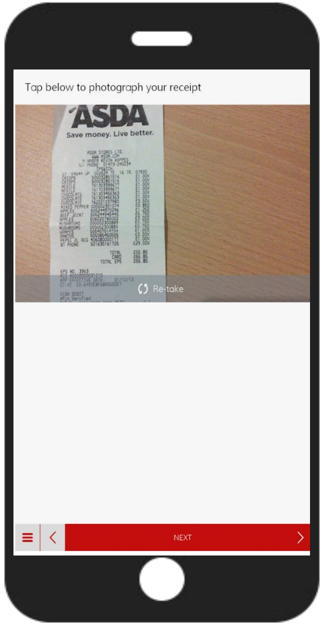
Example: Predicting personality from patterns of smartphone behavior (Stachl et al. 2020)

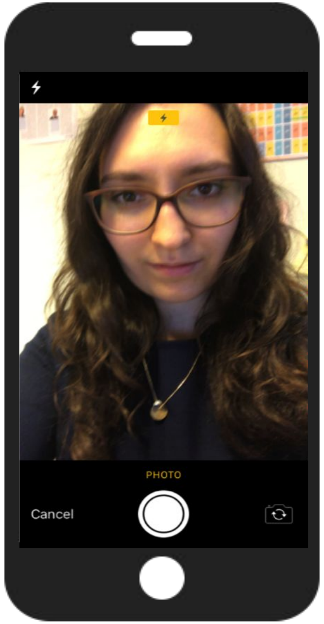
- 743 volunteers in GER completed Big 5 Structure Inventory and collected smartphone usage data via research app over 30 days
- Personality dimensions predicted from six classes of behaviors
  - communication and social behavior
  - music consumption
  - app usage
  - mobility
  - overall phone activity
  - day- and night-time activity



Images

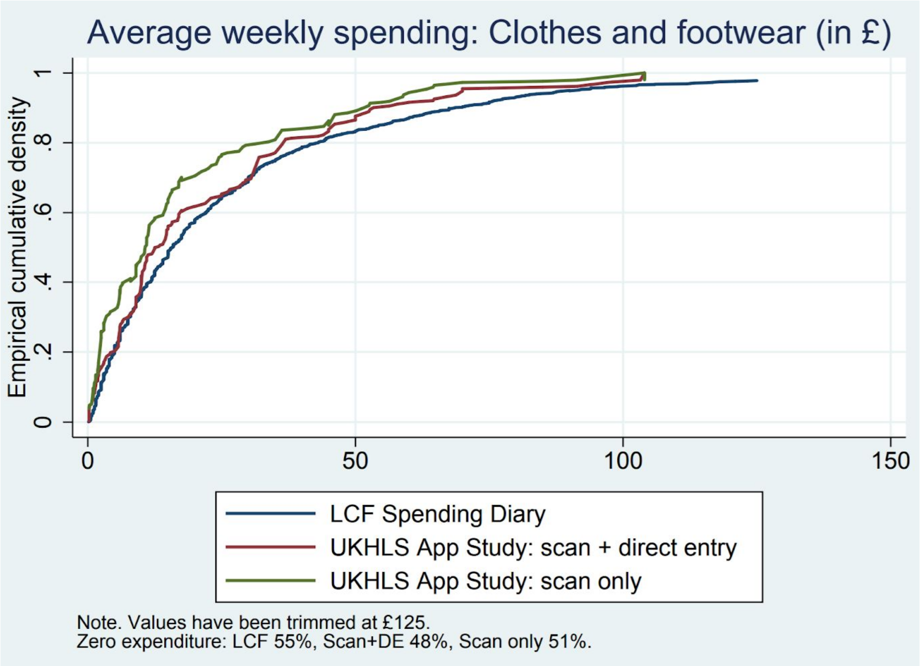
- Photos
  - Food, receipts, physical surroundings, etc.
- Video
- Barcodes
- Linear distance (iPhone Measure app)

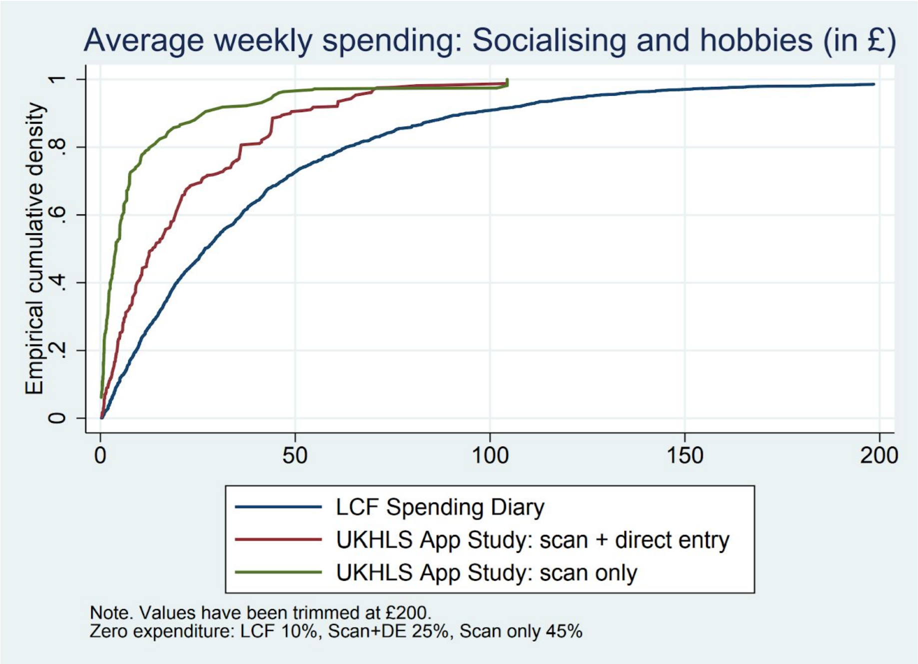




Jäckle et al. (2018)

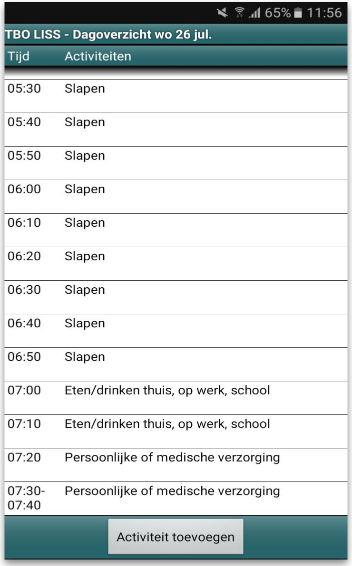
Example: How much do households spend on goods and services? (Jäckle et al. 2019; Wenz et al. 2018)





Self-reports on smartphones

- Diary studies
  - e.g., time use, expenditure, food consumption via app or web browser



Daily overview

Adding activities

Adding activity information

Elevelt et al. (2019)

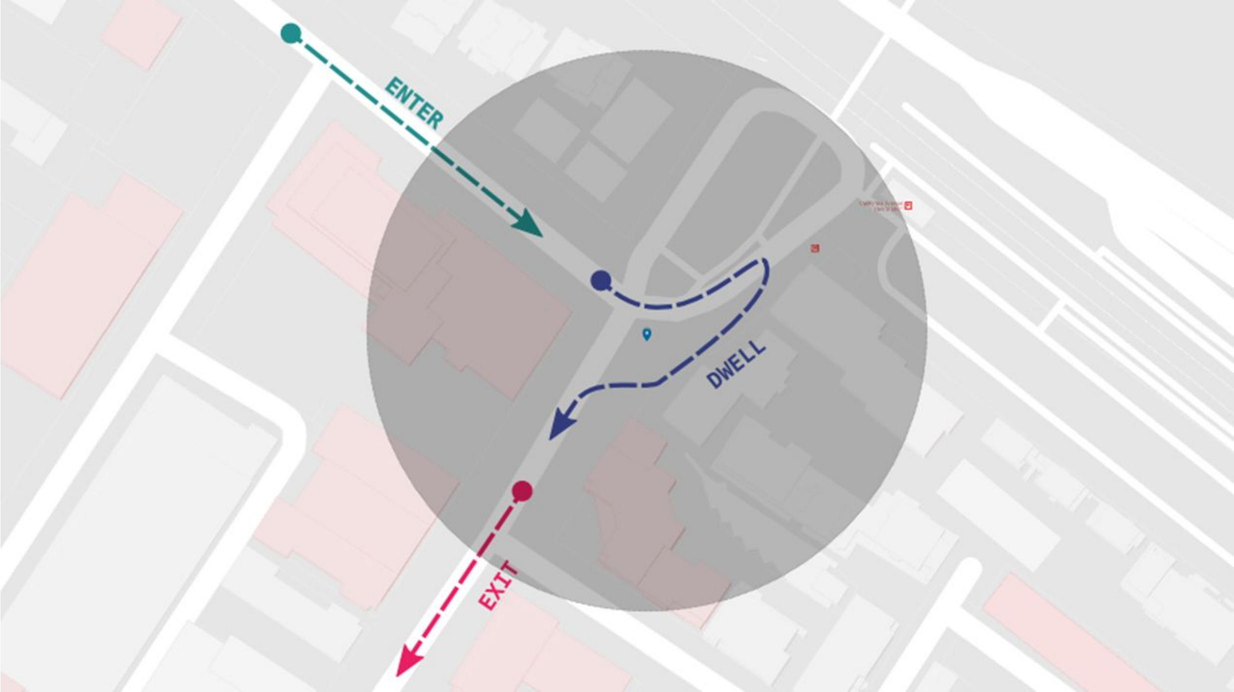
Self-reports on smartphones

- Diary studies (e.g., time use, food consumption) via app or web browser
- Ecological Momentary Assessment (EMA)/Experience Sampling Method (ESM) via app
  - Collecting data several times a day on several days per week allows tracking of change within individuals in much detail
  - Immediate reporting increases ecological validity
  - Participants “pinged” to report about current circumstances
    - Objective situation: e.g., “What are you doing?”
    - Subjective state: e.g., “How anxious are you right now?”
  - Time-based vs. geolocation-based vs. event-based

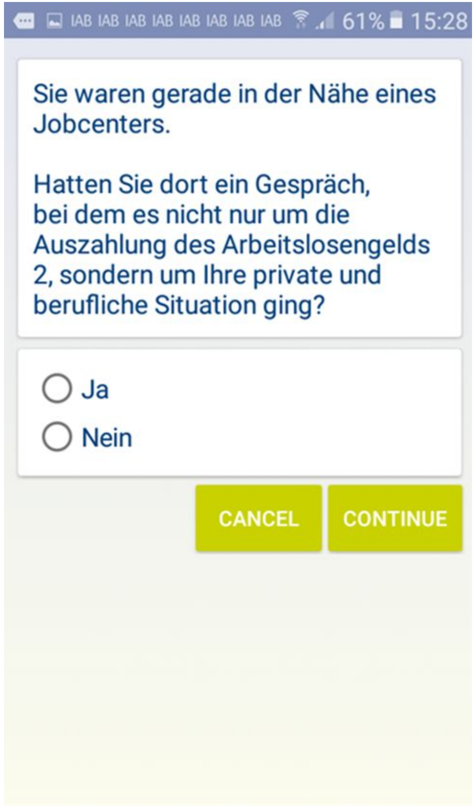
Example time-based EMA: How do environmental factors affect happiness? (MacKerron & Mourato 2013)

- *Mappiness* app installed by ~22,000 self-selected iPhone users and used up to 6 months
- EMA questions: how happy, relaxed, and awake users feel and whom they were with at two or more random points during the day
- Physical setting measured by GPS, appended with information from objective spatial data (broad habitat and land cover type, weather conditions, and daylight status)
- On average, participants significantly and substantially happier outdoors in all green or natural habitat types than in urban environments

Example geolocation-based EMA (“Geofencing”): Visits to job centers (Haas et al. 2020)



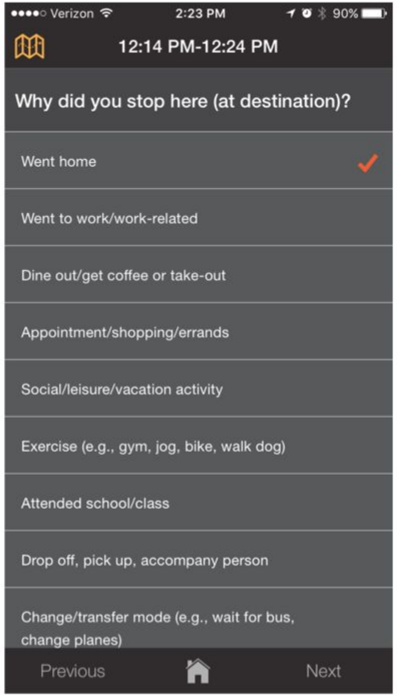
Source: https://developers.google.com/location-context/geofencing/



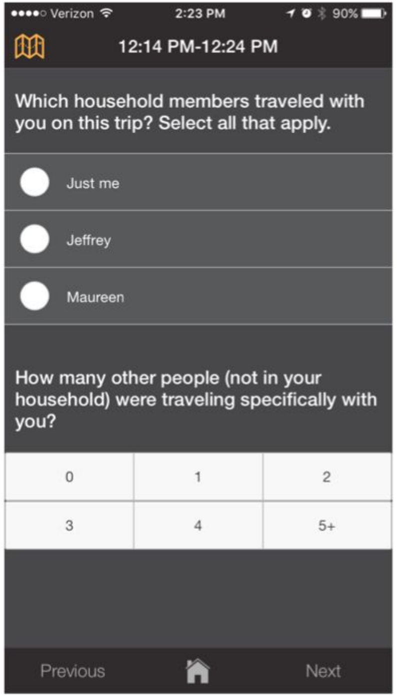
Example event-based: Trip information

(Schmidt et al. 2021)

Trip detection



Stop purpose



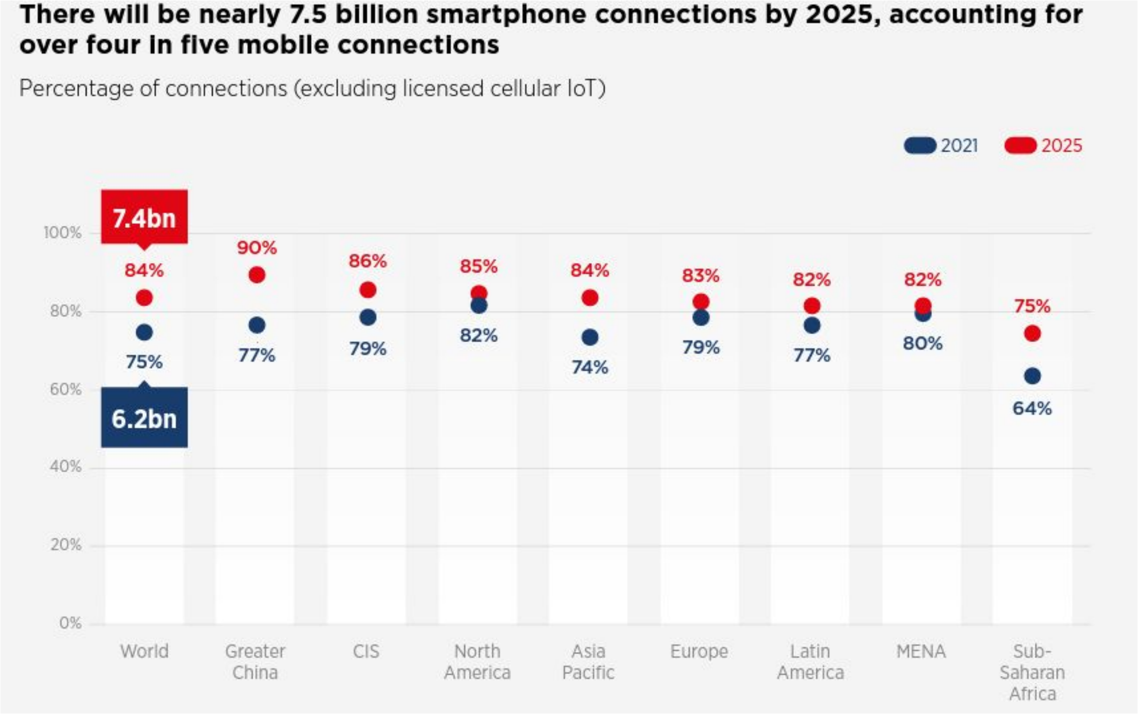
Travel companions

What challenges are there when using wearables, apps, and sensors for data collection

Potential challenges of wearables, apps, & sensors

1. Coverage
    - “Ubiquity Myth” (Couper 2019)
    - Age, education, gender…
    - “2nd-level digital divide”

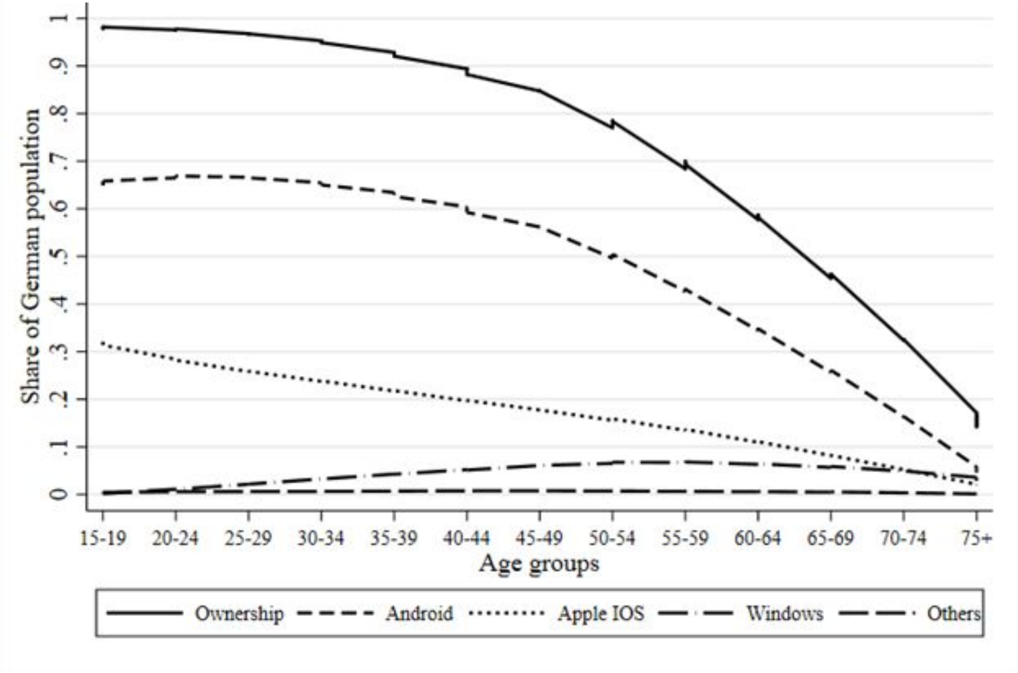
BYOD: Coverage smartphones



Source: https://www.gsma.com/mobileeconomy/wp-content/uploads/2022/02/280222-The-Mobile-Economy-2022.pdf

BYOD: Smartphone coverage bias in Germany

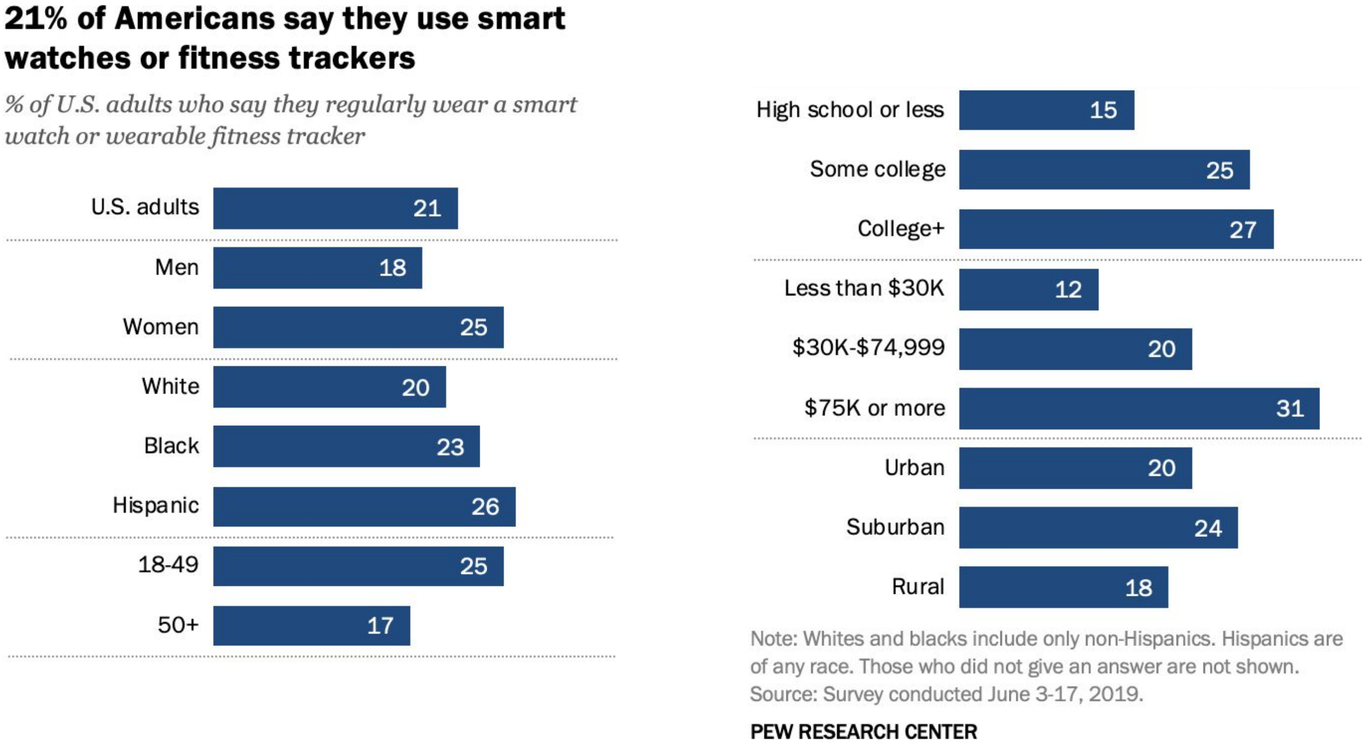
(Keusch et al. 2020)



- Smartphone ownership higher among…
  - …younger
  - …male
  - …higher educated
  - …people in New States
  - …people living in larger communities
- Bias in substantive variables small for general smartphone and Android ownership
  - But large bias for iPhones

Source: PASS Wave 11; n = 13,703; Locally weighted scatter-plot smoother (LOWESS) regression

BYOD: Wearables coverage



Source: https://www.pewresearch.org/fact-tank/2020/01/09/about-one-in-five-americans-use-a-smart-watch-or-fitness-tracker/

Potential solution to coverage problem: Provide (loaner) devices

Pros

- Increasing coverage
- Standardizing measurement (e.g., iOS vs. Android, Fitbit vs. Apple watch)
- Use specifically configured devices
- Research-grade devices for better measurement (e.g., Actigraph, Hexoskin)

Cons

- Potential health concerns
- Ensuring compliance
- High costs for devices (e.g., as incentives or sent in batches) and management/ implementation
- Potential reactivity

Potential challenges of wearables, aps, & sensors

1. Coverage
2. Nonparticipation
    - Willingness
    - Ability
    - Adherence to study protocols

Mechanisms on (non-)participation

- WTP increases with **incentives** (Keusch et al. 2019; Wenz & Keusch in press); bonus incentives have little effect (Haas et al. 2021; McCool et al. 2021)
- WTP higher for tasks where participants have **agency** over data collection (Revilla et al. 2019; Keusch et al. 2019; Struminskaya et al. 2020; 2021; Wenz & Keusch in press)
- WTP higher for university **sponsor** vs. market research and statistical office (Keusch et al. 2019; Struminskaya et al. 2020)
- **Smartphone skills**: more activities on smartphone (e.g., using GPS, taking pictures, online banking, etc.) correlates with higher WTP (Keusch et al. 2019; Struminskaya et al. 2020; 2021; Wenz et al. 2019; Wenz & Keusch in press)
- Prior **experience** with research app download increases WTP (Keusch et al. 2019; Struminskaya et al. 2020; 2021)
- **Education** (Jäckle et al. 2019; Keusch et al. 2021, 2022; McCool et al. 2021; Wenz & Keusch in press) and **age** (Jäckle et al. 2019; McCool et al. 2021; Keusch et al. 2022; Wenz & Keusch in press) correlated with WTP

Non-participation for (loaner) wearables (Actigraphy, Fitbit, etc.)

- Must consider both *Consent Rate* and *Compliance Rate*
- Compliance can be for full study duration (all days, all hours) or partial (some days, some hours)
- Reasons for non-participation include:
  - Device not visually appealing
  - Device uncomfortable
  - Device removed (at night or to shower) and not put back on
  - Battery runs out
  - Data does not sync (calibration error, syncing error)
  - Device lost
  - Device not returned
  - ...

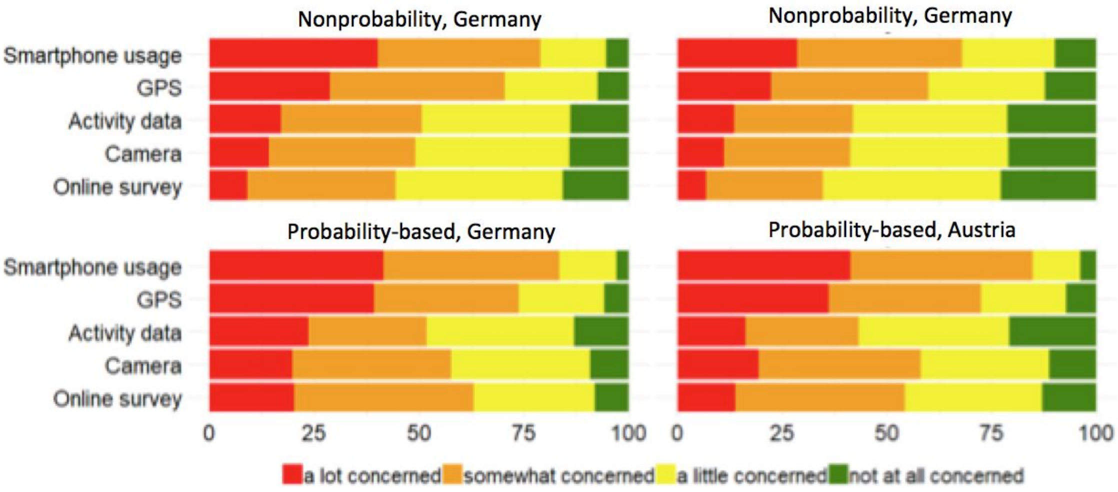
Toepoel (2021)

Potential challenges of wearables, aps, & sensors

1. Coverage
2. Nonparticipation
3. Privacy & ethics
   - What concerns do people have?
   - “Privacy paradox”

Privacy concern

- Many people express concern about potential risks related to sensor data
- Higher privacy & security concerns correlate with lower WTP (Keusch, et al. 2019; Revilla et al. 2019; Struminskaya et al. 2020; 2021; Wenz et al. 2019; Wenz & Keusch in press)



Keusch et al. (2021)

Consent

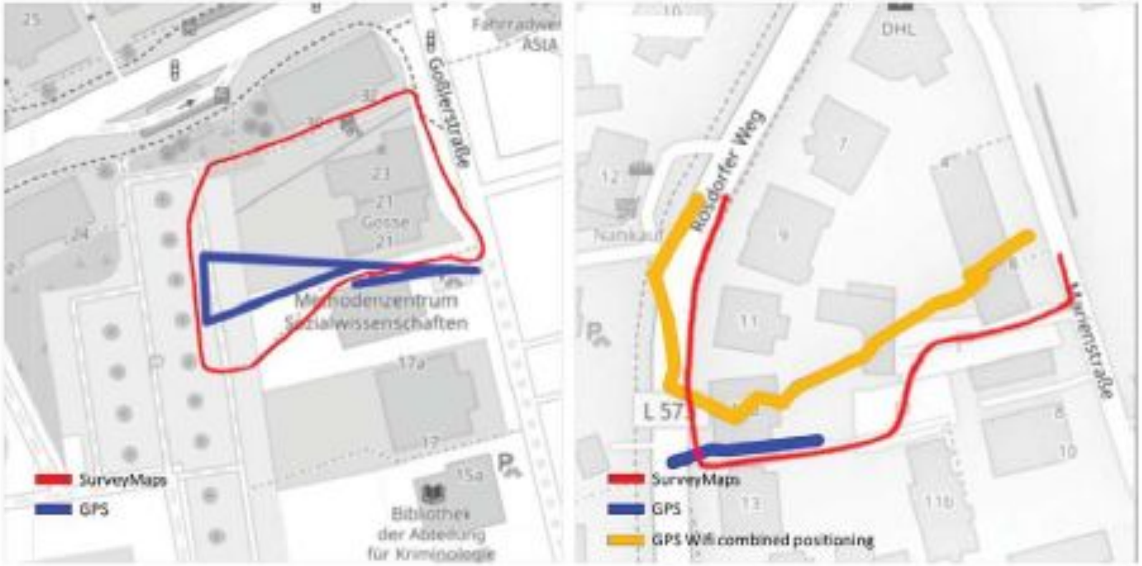
- Ethics
  - “Informed consent”
  - IRB approval
- Legal
  - Depends on type of data collected (e.g., PII, GDPR, DPIA)
  - Talk to legal department early!
- Technical implementation
  - Depends on device, OS, and researcher choices

Potential challenges of wearables, aps, & sensors

1. Coverage
2. Nonparticipation
3. Privacy & ethics
4. Measurement
    - Tempting to assume that by removing human cognition and social interaction from "passive" sensor data collection, we eliminate all measurement error
    - But errors might still arise when collecting, processing, and interpreting data

Errors during data collection

- Sensor-based errors/differences
    - Differences between types of sensors as well as brands and models of devices
    - Not one sensor/device per se better than others, depends on what should be measured under what circumstances



Schlosser et al. (2019)

Errors during data collection

- Sensor-based errors/differences
- Device handling
  - Measurement might differ depending on where/ how sensor/device is worn
    - e.g., differences in how men and women carry around smartphones
  - Do people use device as anticipated by research?

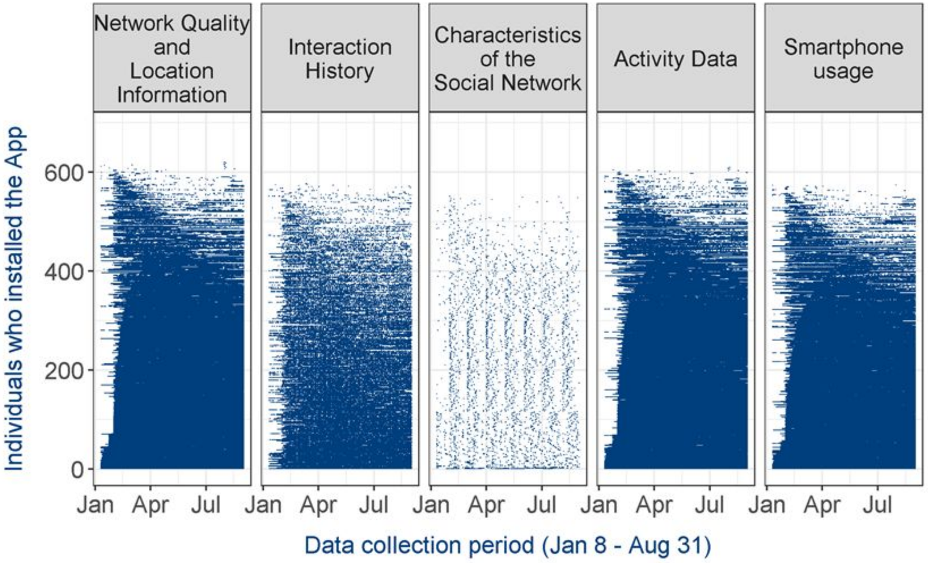
Sztyler et al. (2017)

Errors during data collection (Keusch et al. 2022)

Behavioral barriers – Smartphone...	Sample 1	Sample 2
...shared with another person	2%	1%
...not always on	32%	44%
...left at home	17%	14%
...carried in purse/backpack/bag when not at home	46%	30%
...left stationary when at home and not asleep	66%	47%
...turned off or in other room at night	49%	34%
n	3,956	2,525

Errors during data collection

- Sensor-based errors
- Device handling
- Missing data
  - Technical issues:
    - Urban canyons, underground, etc. when collecting GPS
    - Device out of power or sleep mode
    - iOS blocks collection of location in background
    - …
  - Noncompliance:
    - Leaving device at home
    - Deliberately turning device off at certain locations or times
    - Forgetting to turn device back on again
    - Missing permissions
    - …



Errors during data collection

- Sensor-based errors
- Device handling
- Missing data
- Providing feedback & measurement reactivity
    - e.g., participants show 7% more physical activity when wearing Fitbit (with feedback) compared to when wearing GENEActive (no feedback) (Darling et al. 2021)

Source: https://twitter.com/mbrennanchina/status/1128201958962032641

Errors during processing & interpretation

- Raw sensor data must be processed and classified to infer behavior
- “Black box” approach when using third-party algorithm to classify data on device
    - What looks like raw data to researcher is actually (heavily) pre-processed
    - e.g., activity classification was trained based on data from young adults (“WEIRDOS” ©Mick P. Couper) → used to classify behavior of general population
    - e.g., smartphone forgotten at home in a bag → respondent is asleep
- Self-report still needed for validation

Q & A

If you have questions, need more information, or want to collaborate…

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Also, please check out our book:

Keusch, Florian, Bella Struminskaya, Stephanie Eckman, and Heidi Guyer. forthcoming. *Data Collection with Wearables, Apps, and Sensors.* https://bookdown.org/wasbook_feedback/was/

Additional resources

Selected resources for app development

- Commercial/Off-the-shelf existing platforms
  - Movisens: https://www.movisens.com/en/
  - MOTUS: https://www.motusresearch.io/en
  - Murmuras: https://murmuras.com/

- Commercial app builders (usually no special knowledge required)
  - Appypie https://www.appypie.com
  - Ethica Data: https://ethicadata.com/

Selected resources for app development

- App builders for specific OSs (require some programming knowledge)
  - Apple Research Kit: http://researchkit.org/
  - ResearchStack for Android: http://researchstack.org/

- Open source platforms/frameworks (require programming knowledge)
  - AWARE: https://awareframework.com/
  - Beiwe Research Platform: https://www.beiwe.org/
  - PACO: https://pacoapp.com/

Selected resources for EMA/ESM

- Specific EMA/ESM software
  - mEMA: https://ilumivu.com
  - ExpiWell: https://www.expiwell.com/
  - LifeData: https://www.lifedatacorp.com/ecological-momentary-assessment-app-2/
  - SEMA3: https://sema3.com/
  - Other online survey software, such as Blaise5 (https://blaise.com/products/blaise-5), can be used as sample management system that can send surveys at specific time
- Myin-Germeys, Inez, and Peter Kuppens. (Eds.). 2022. *The open handbook of experience sampling methodology: A step-by-step guide to designing, conducting, and analyzing ESM studies.* (2nd ed.) Leuven: Center for Research on Experience Sampling and Ambulatory Methods Leuven

Other resources

- For visualization of location data:
  - Shiny app Utrecht University (R code): https://github.com/sobradob/shinyapp
- For data processing:
  - R package for log data analysis (Stachl): https://osf.io/ut42y/

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