Using Smartphones for Passive and Active Data Collection in Older Populations

NETWORK FOR INNOVATIVE METHODS IN LONGITUDINAL AGING STUDIES
UNIVERSITY OF MICHIGAN

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NIMLAS Workshop, February 8, 2023

Agenda

- Introduction
- Why use smartphones for data collection?
- What can we measure with smartphones?
- Study design considerations from a TSE perspective
- Additional resources

Acknowledgement

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

Introduction

Who are you?

Exercise

What sensors does your smartphone have?

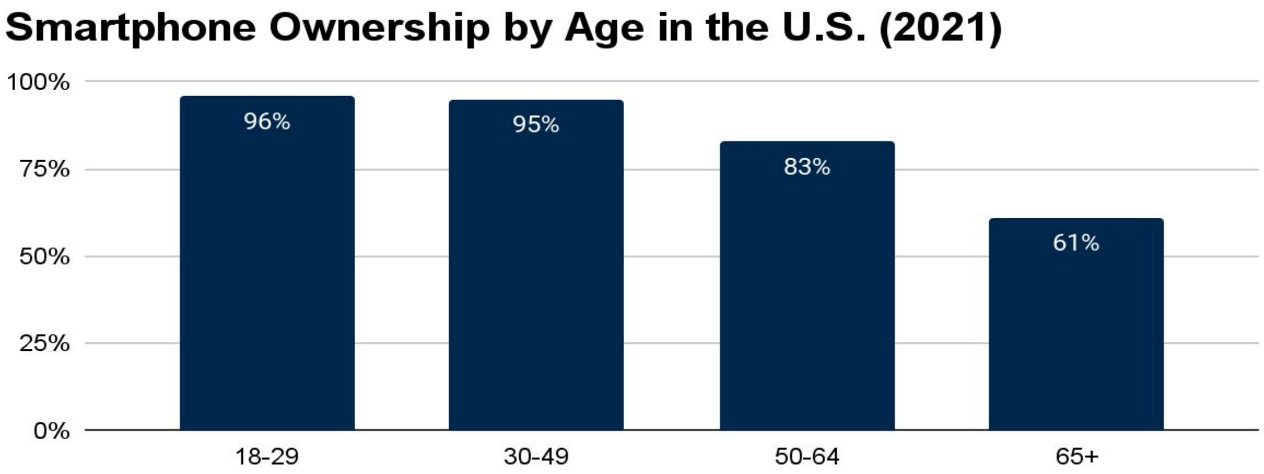
Disclaimer

- Smartphones are an exciting tool for collecting data with many advantages over traditional data collection in social sciences
- As with all methods, need to consider errors and costs of using smartphones for specific research question in specific target population
- Workshop will provide overview of possibilities and limitations in using smartphones among older adults
- Smartphones might not be right tool for some target populations (e.g., people with dementia)

Why use smartphones for data collection?

Potential benefits of smartphones

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



Source: https://www.pewresearch.org/internet/fact-sheet/mobile/#who-owns-cellphones-and-smartphone

Potential benefits of smartphones

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 smartphones

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

Potential benefits of smartphones

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 smartphones

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 smartphones

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 (MacKarron & Murrato 2013)
   - 650 members of existing longitudinal study downloaded *IAB-SMART* app and responded to mini-surveys plus shared location, physical activity, and smartphone use data for 6 months (Kreuter et al. 2020)

Potential benefits of smartphones

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 (?)

Potential challenges of smartphones

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

Potential challenges of smartphones

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

Potential challenges of smartphones

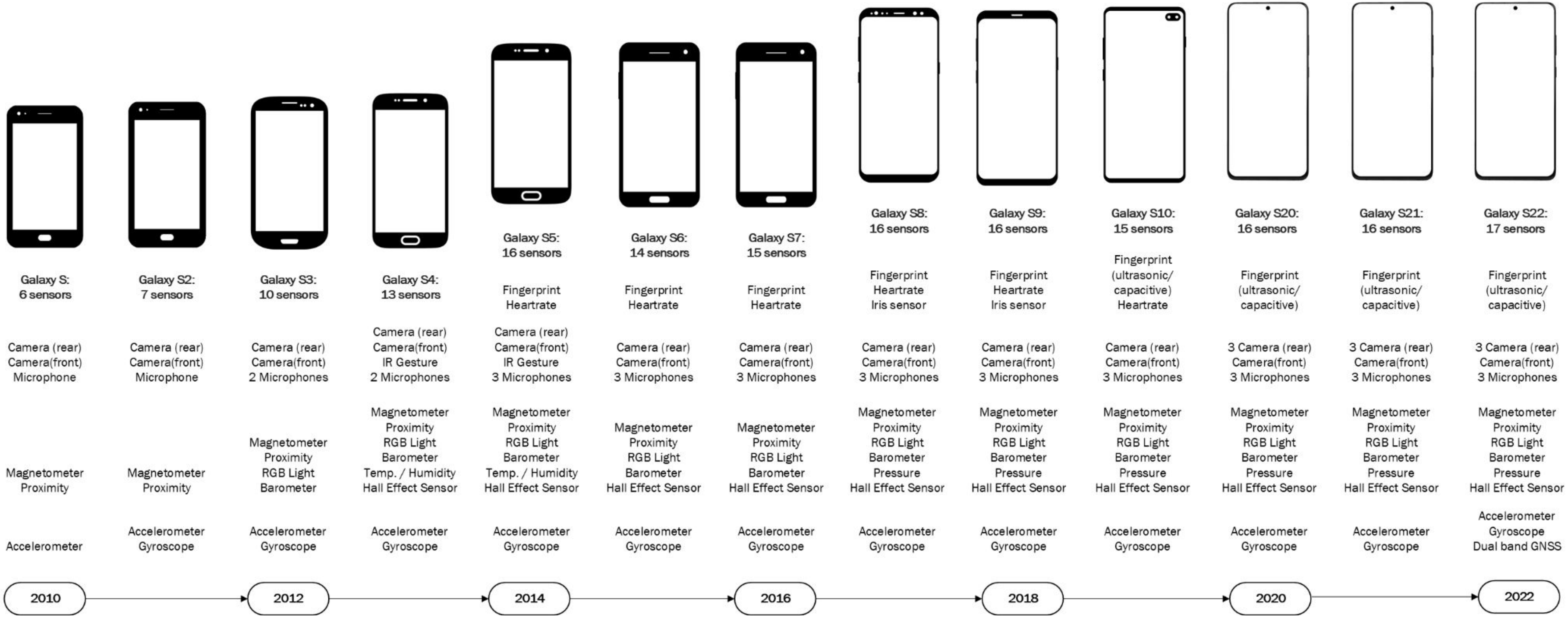
1. Coverage
2. Nonparticipation
3. Privacy & ethics
    - What concerns do people have?
    - “Privacy paradox”

Potential challenges of smartphones

1. Coverage
2. Nonparticipation
3. Privacy & ethics
4. Measurement
    - Data not free of error
    - Technical issues and human behavior can lead to missings and implausible readings

What can we measure with smartphones?

Smartphones & sensors



Struminskaya & Keusch. (2023)

Native smartphone sensors

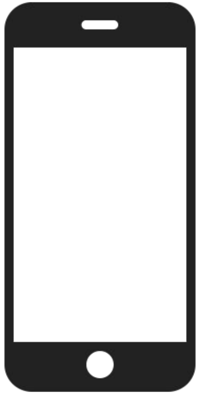
NFC

Heart rate sensor

Bluetooth

Air humidity sensor

Thermometer



Proximity sensor

Wi-Fi

Microphone

GPS

Light sensor

Cellular network

Fingerprint sensor

Camera

Barometer

Compass

Accelerometer

Pedometer

Gyroscope

Native smartphone sensors

Proximity

NFC

Bluetooth

Heart rate sensor

Air humidity sensor

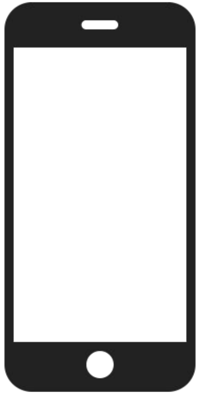
Thermometer

Location

Wi-Fi

GPS

Cellular network



Proximity sensor

Microphone

Light sensor

Ambience/ Environment

Camera

Fingerprint sensor

Barometer

Compass

Accelerometer

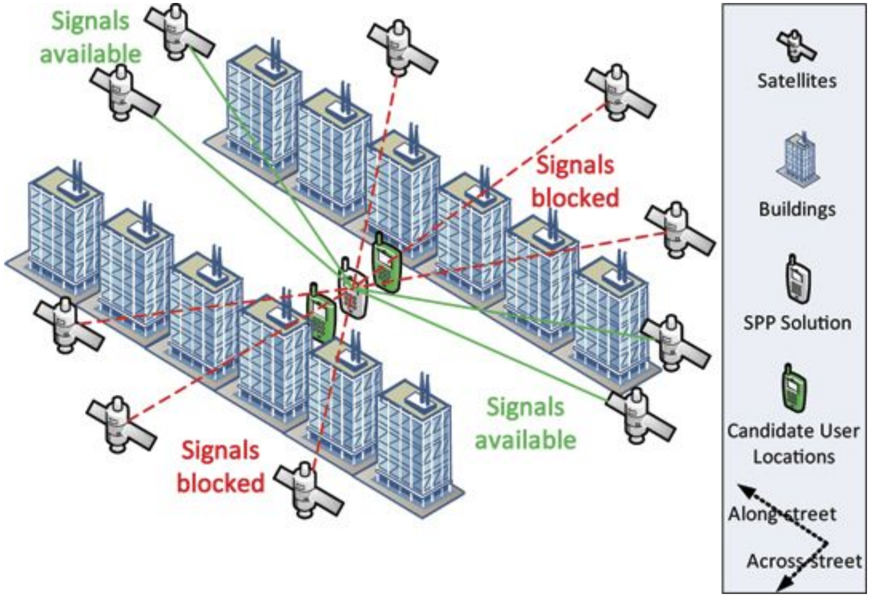
Pedometer

Gyroscope

Physical activity

Geolocation

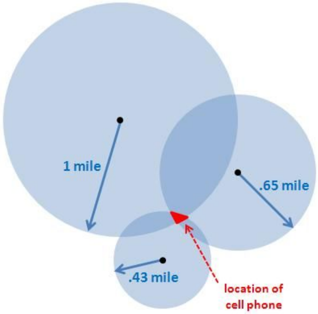
- GPS
  - Provides coordinates in longitude & Latitude
  - Based on distance (= rate x time) to at least 4 satellites
  - Newest generation has accuracy within 30 centimeters
  - Works without cell/Internet connection
  - Performs worse in ‘urban canyons’, indoors, & underground
  - Constant tracking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



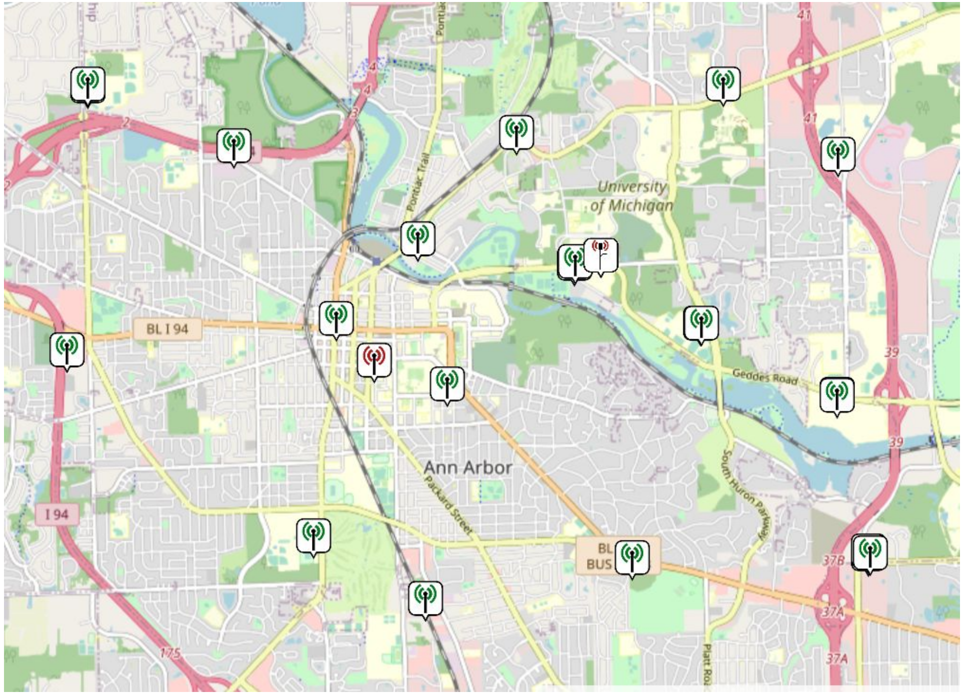
Source: https://www.gpsworld.com/wirelesspersonal-navigationshadow-matching-12550/

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



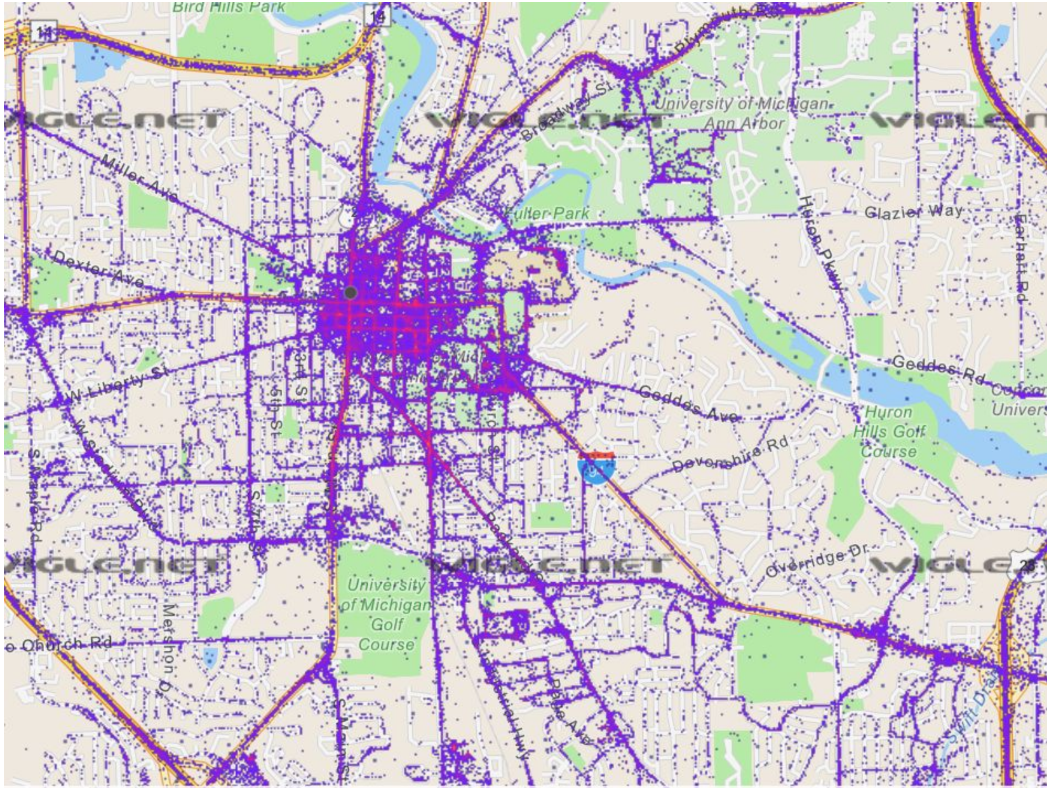
Source: https://searchengineland.com/cell-phone-triangulation-accuracy-is-all-over-the-map-14790



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

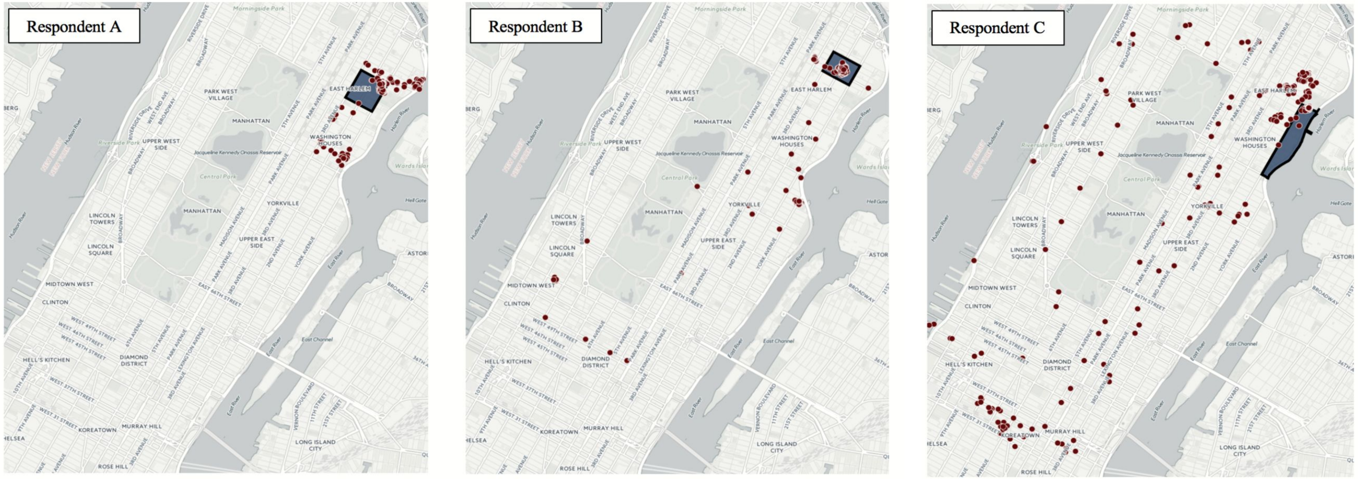
Geolocation

- GPS
- Cellular network
- Wi-Fi
- Hybrid positioning systems
  - 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



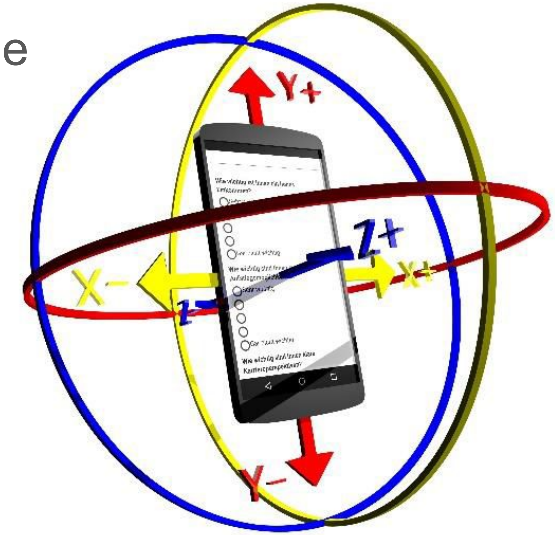
Example: Aging in activity space (Results)

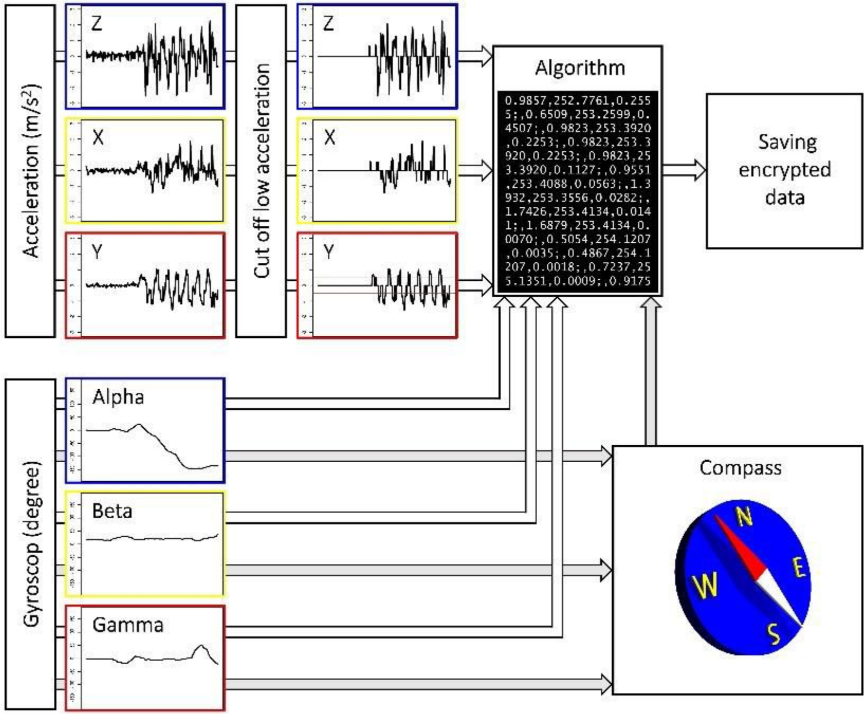
(York Cornwell & Cagney 2017, 2020)

- Activity spaces vary considerably in size
- Participants spent ~40% of their time outside their residential tracts
    - On average >10 min in 9+ tracts
- Activity spaces larger among younger and more advantaged social groups (i.e., whites, those with college degree, car owners)
- Participants with less education and lower incomes spend more time outside of their residential tracts
- Four main activities outside of residential tracts
    - Shopping, exercising, socializing, participating in social groups or activities
- Poverty rates in nonresidential tracts lower than in residential tracts
- Higher concentrated disadvantage in an area associated with higher odds of self-reporting pain

Physical activity

- Accelerometer
- Gyroscope





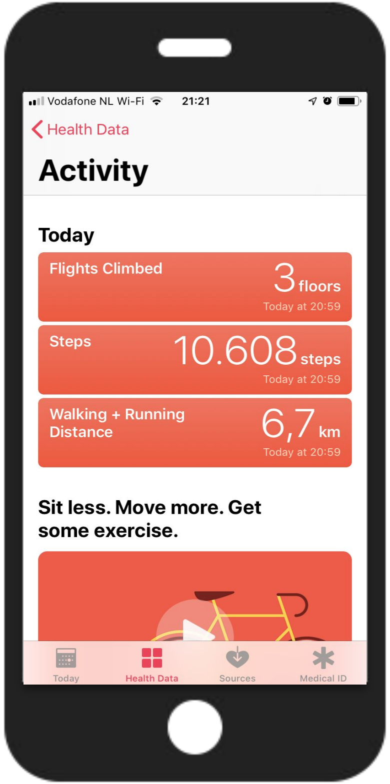
Schlosser et al. (2019)

Physical activity

- Accelerometer
- Gyroscope

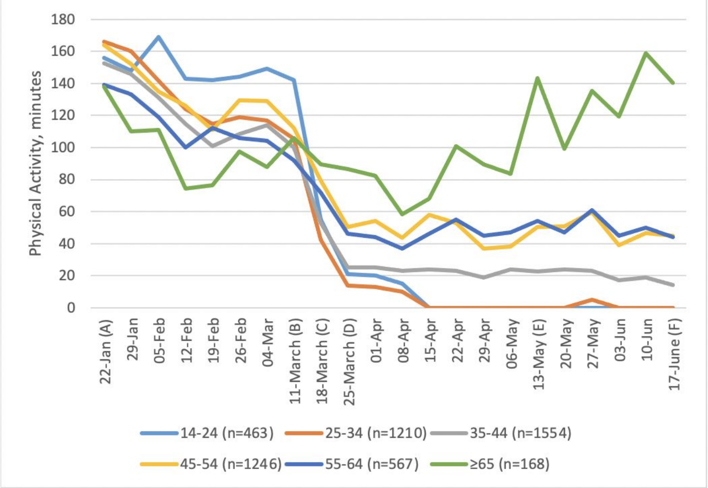
and

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



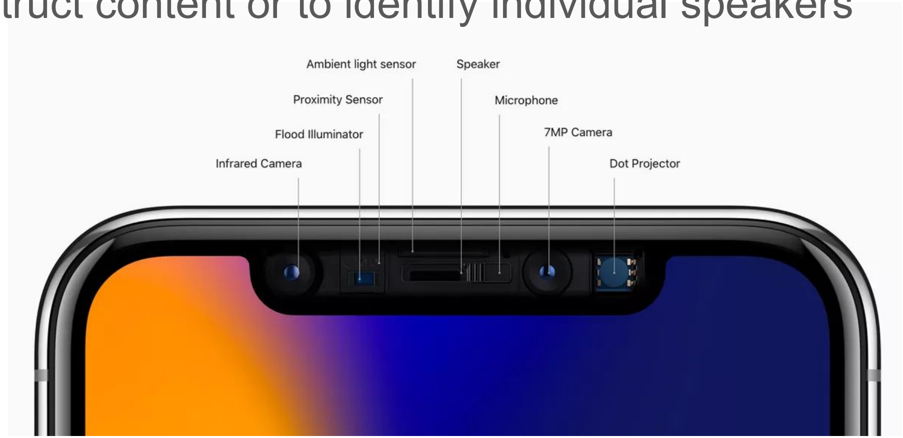
Example: Physical activity behavior before, during, and after COVID-19 restrictions (McCarthy et al. 2021)

- Weekly minutes of (outdoor) PA of 5,395 existing UK users of *BetterPoints* smartphone app tracked between January and June 2020
- Results:
  - Significant decreases in PA at all time points throughout lockdown period
  - Those who were most active before lockdown showed biggest falls in PA
  - Older participants showed less decrease in PA at start of lockdown and greater increase as lockdown continued



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

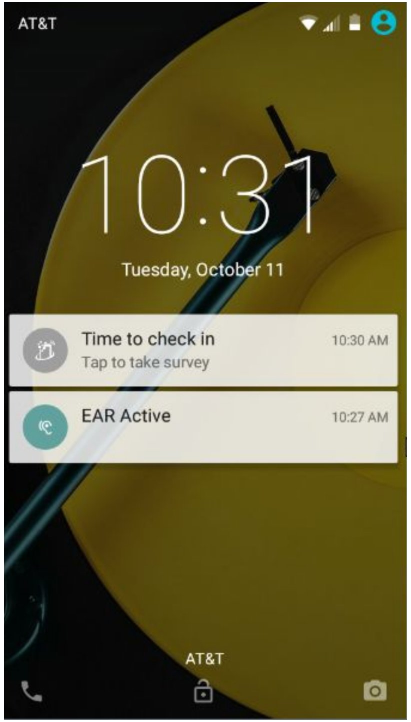


Source: https://www.theverge.com/circuitbreaker/2017/9/15/16307802/apple-iphone-x-features-specs-best-worst

Example: *Daily Experiences and Well-being* Study

(Fingerman et al. 2020)

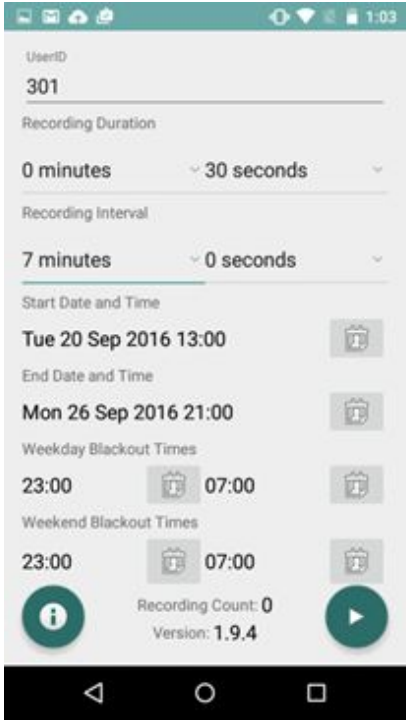
- Telephone screening to identify home-dwelling aged 65+ in Austin, TX (n=333)
  - Oversample of Blacks and Hispanics
  - Without cognitive impairment, not working full-time
- Goal: Study influence of social engagement on physical activity, health, and cognitive status
- In-home interview followed by 5 days of:
  - Actigraphy
  - Loaner Android device with apps to record sound and prompt for ecological momentary assessment (EMA) - no other smartphone functionality
- Daily reminder phone calls & in-home assistance



Example: Electronically Activated Recorder (EAR)

(Fingerman et al. 2022)

- During in-home interview, interviewers entered settings in *EAR* app on phone
  - 30s of recordings every 7 min during waking hours
  - Total of 135,078 audio files
- Devices obtained by interviewer on day 5
- Interviewers responsible for upload and transfer of all data from various devices
- Coders rated each file containing sound for presence of television
- Findings:
  - More TV watching when alone
  - More loneliness reported during periods of TV watching

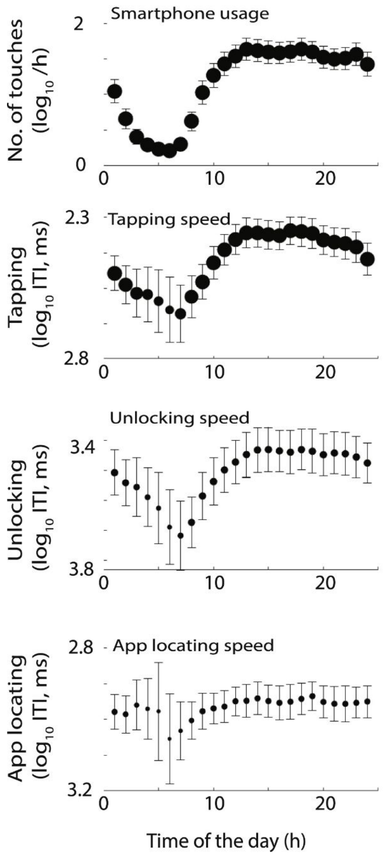


Digital phenotyping

- 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

Use case: Capturing sleep-wake cycles via tappigraphy (Borger et al. 2019; Huber & Gosh 2021)

- 189 Dutch Android smartphone users (under age 45) recorded day-to-day smartphone touchscreen interactions via *TapCounter* app over 3 weeks
  - No. of touchscreen interactions, tapping speed, unlocking speed, app locating speed
- Results:
  - Smartphone touches yield reliable proxy measure of sleep verified by actigraphy and sleep diaries
  - Digital interactions are part of falling asleep and waking up
- Tappigraphy also used as proxy for cognitive status in perioperative setting of brain tumor surgery (Akeret et al. 2020)



Proximity - Bluetooth

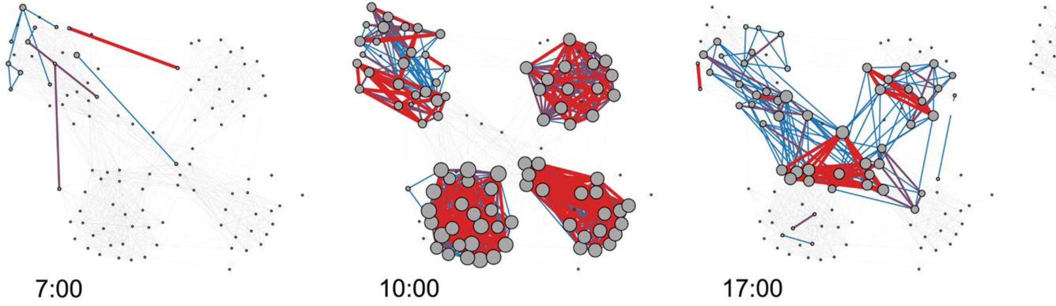
- Short-range communication between devices up to 30 m
  - e.g., hands-free devices, audio speakers, printers
- Enabled healthcare devices can connect to smartphones or other hubs to transmit data
  - e.g., weight, blood pressure, temperature, heart rate, etc.
- Beacons = small Bluetooth transmitters
  - 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

Jud (2018)

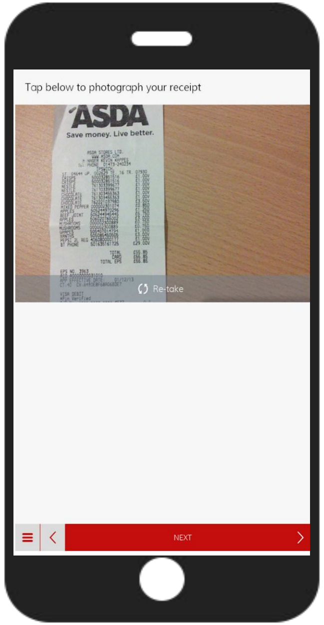
Example: How do people interact in large social networks? (Stopczynski et al. 2014)

- *Copenhagen Networks Study* handed out ~1,000 smartphones to Danish university students
- Extensive questionnaire upon enrollment: 310 questions on topics from public health, psychology, anthropology, and economics
- Combination of Bluetooth and Wi-Fi networks to collect information about absolute location and relative location to each other



Camera

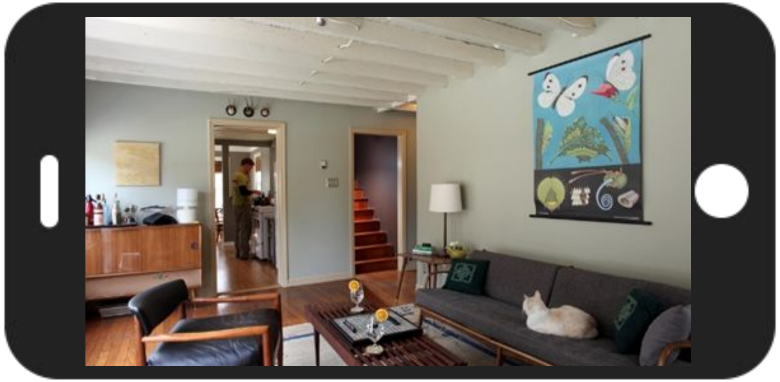
- Photos
  - Food, receipts, physical surroundings, etc.
- Video
- Barcodes
- Linear distance (iPhone Measure app)



Jäckle et al. (2019)

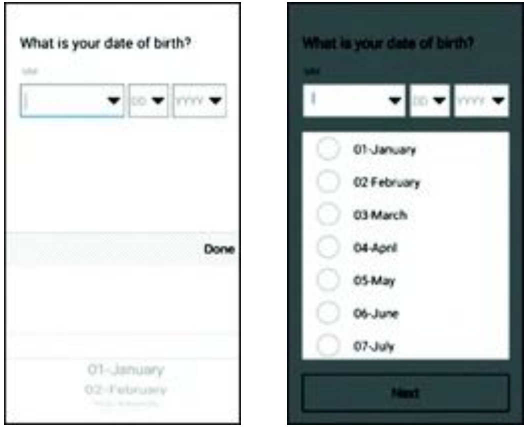
Example: Taking pictures of surrounding

- *Daily Experiences and Well-being Study* (Fingerman et al. 2020)
- Interviewers used phone app when returning to pick device up (day 5)
- After completing all other activities, asked participant for consent to take picture of room they spend most time in
  - Up to 3 photos
  - Careful selection of motive to avoid recording any PII
- Environmental conditions of room hand-coded
  - Lighting, conditions, etc.

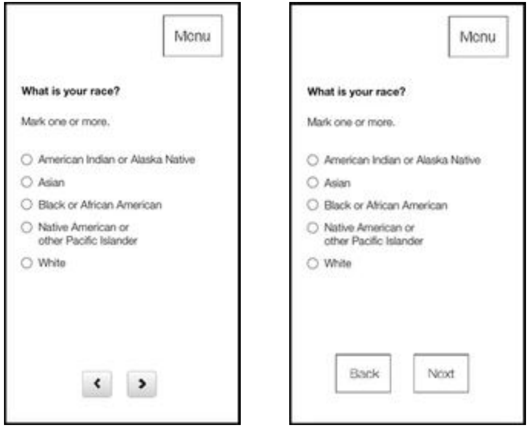


Self-reports on smartphones

- “Traditional” mobile web surveys
  - Invitations via e-mail, text message, QR code, printed URL, …
  - General design considerations for mobile web surveys (Antoun et al. 2018)
  - Specific design recommendations for older adults (Olmsted-Hawala et al. 2018)
    - Avoid default iOS picker design and use Android spinner style or keyboard
    - Always label forward and backward navigation buttons using text rather than icons



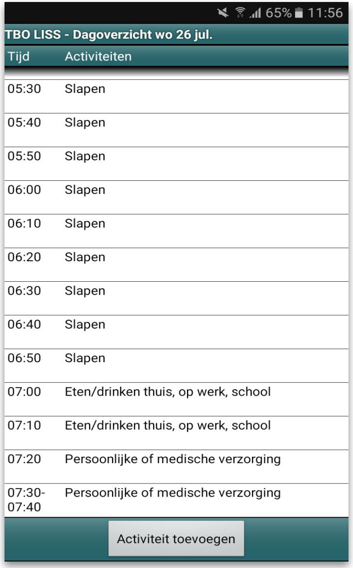
Olmstedal-Hawala et al. (2019)



Olmstedal-Hawala et al. (2019)

Self-reports on smartphones

- “Traditional” mobile web surveys
- Diary studies (e.g., time use, food consumption) via app (or web browser)



Daily overview

Adding activities

Adding activity information

Elevelt et al. (2019)

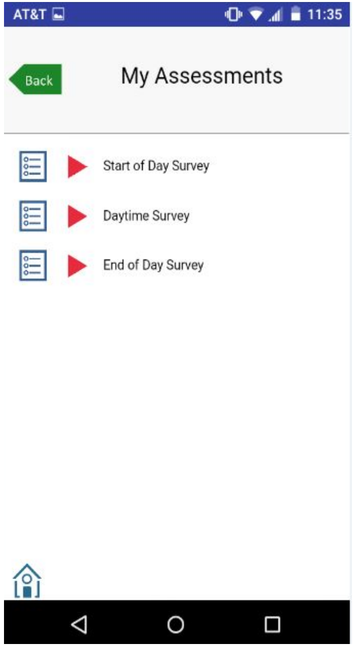
Self-reports on smartphones

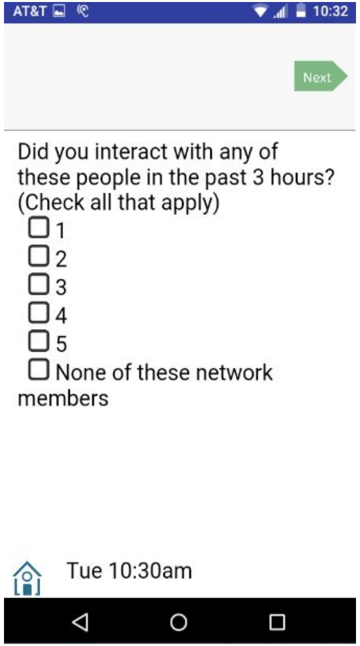
- "Traditional" mobile web surveys
- Diary studies (e.g., time use, food consumption) via app or web browser
- Ecological Momentary Assessment (EMA)/Experience Sampling Method (ESM) via app
    - Collecting data several times a day on several days per week allows tracking of change within individuals 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: Do social connections influence health and well-being?

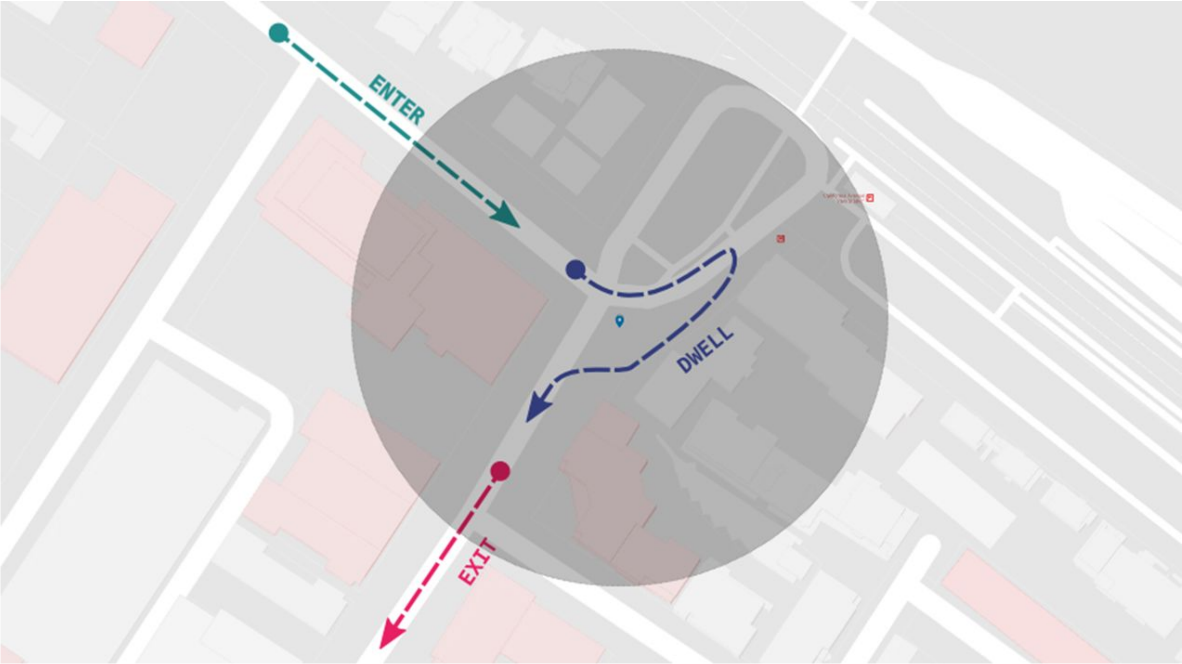
(Fingerman et al. 2020, 2022; Hou et al. 2020)

- EMA to complete every 3 hours for 5 days
- Questions on…
  - Social interactions with people in core support network
  - Frequency, type, and duration of 14 sets of waking behaviors
  - Mood (positive and negative emotions)

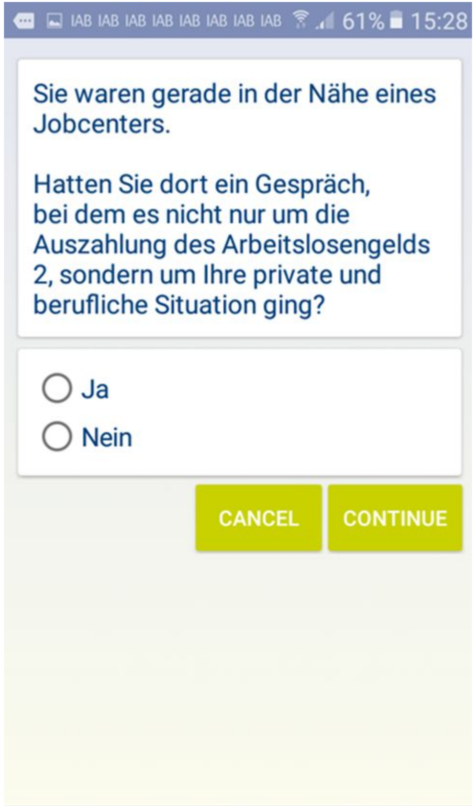




Example geolocation-based EMA ("Geofencing"): Visits to job centers (Haas et al. 2020)



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

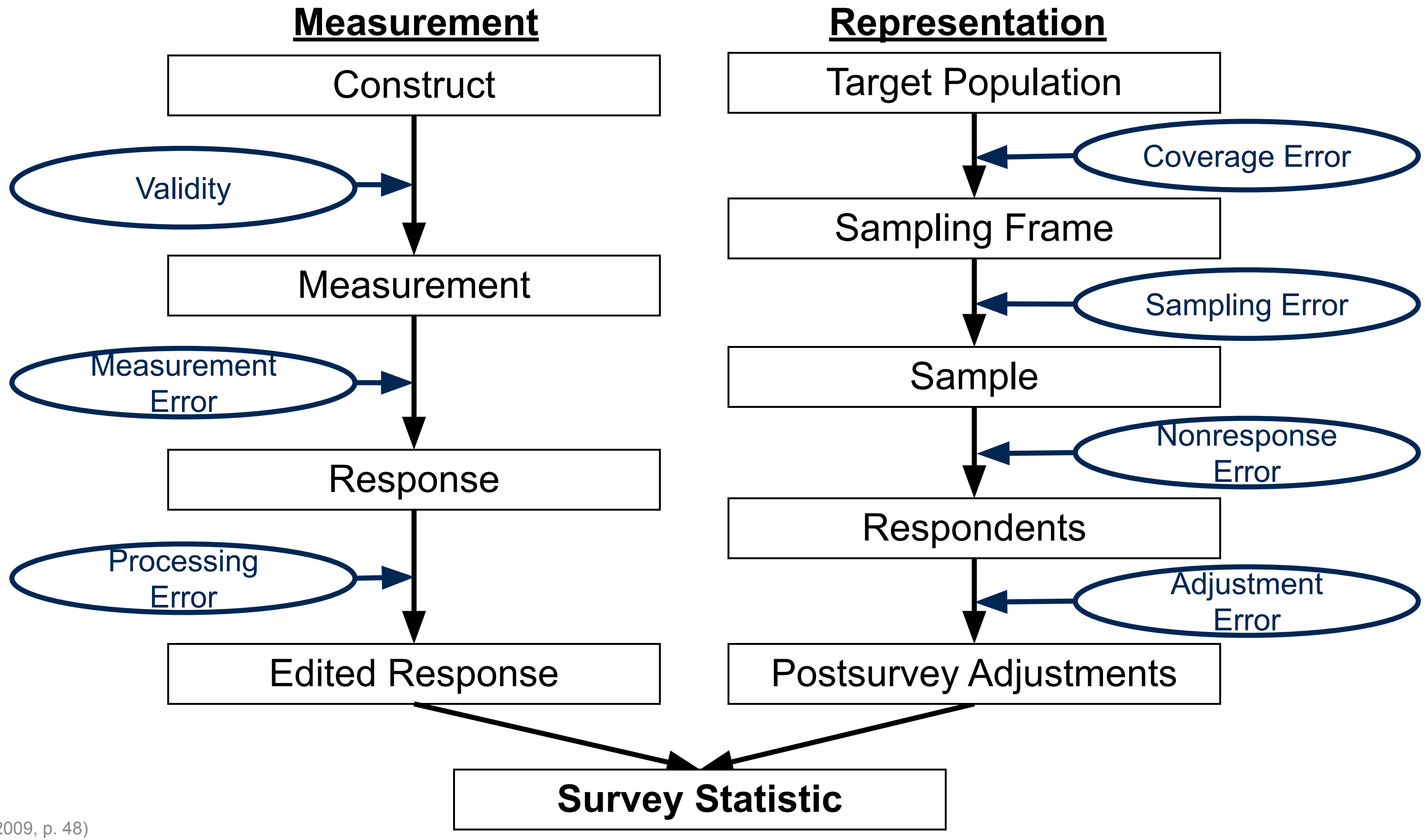


Exercise

Thinking about the target groups you usually work with in your research, what could be concrete challenges when using smartphones for data collection?

Study design considerations from a Total Survey Error perspective

Total survey error (TSE) framework

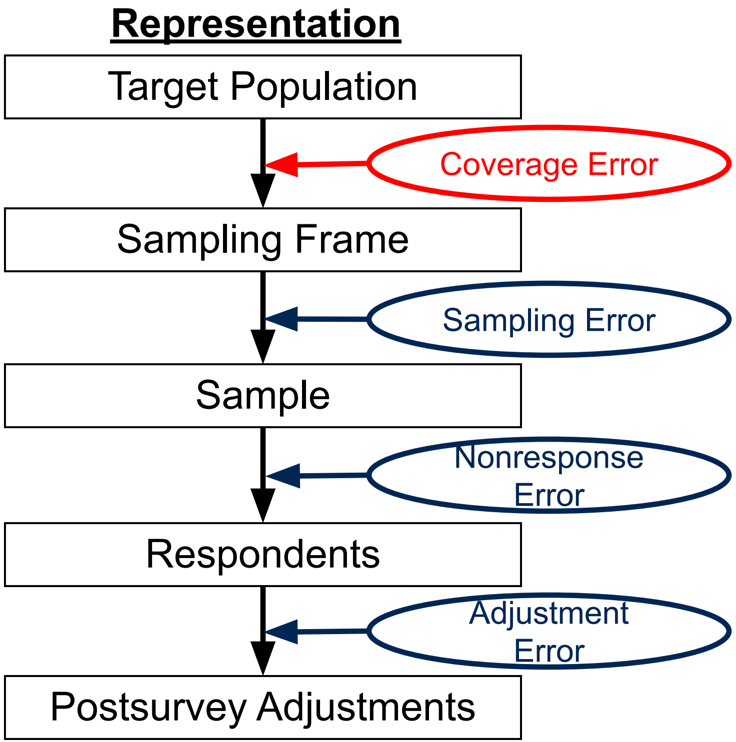


Groves et al. (2009, p. 48)

Total survey error (TSE) framework

- Concept, way of thinking about various sources of error that may affect survey statistics
- “Error” ≠ “mistake”, rather uncertainty (or lack of confidence) of inference
- Design each component of study to minimize error inherent to that component
- Assess level of error associated with alternative procedures and choose combination of approaches best suited to problem
- Errors can arise from many sources
  - Topic, available funding, sampling frame, data collection method, etc.
- In sum, notion of TSE guides design decisions
  - TSE framework helps understanding potential impact of design decisions on errors
  - Together with costs, explicit part of design decisions

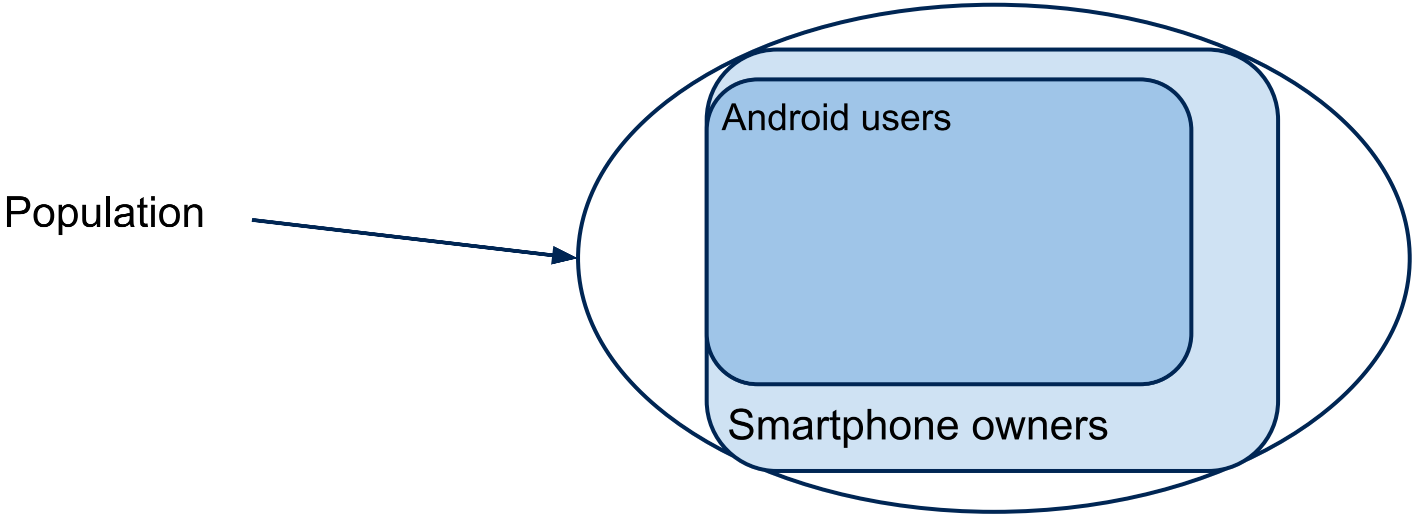
Representation error in smartphone data collection



- **Coverage error:** A study of older adults relies on participants to provide data from their own smartphones to analyze weekend vs. weekday activity by sociodemographic groups. The rate of ownership of smartphones decreases with age; so does the amount of activity.

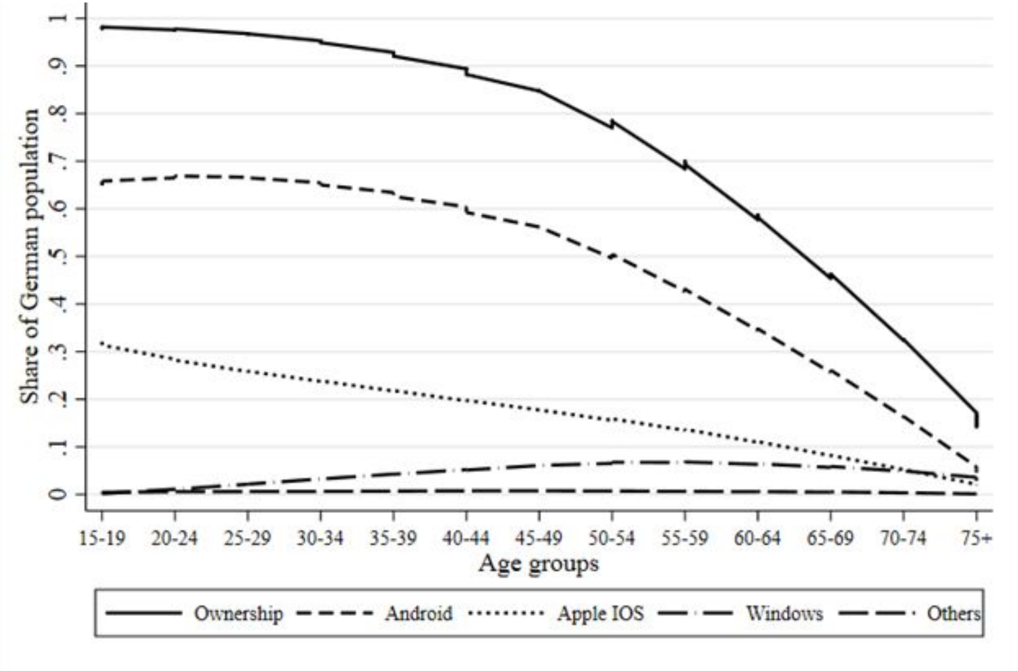
To participate in a smartphone study, one needs to…

- …have access to a (specific) smartphone → (potential) Coverage error



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

➢ Digital Divide

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

BYOD: Smartphone coverage bias in Germany

(Keusch et al. 2020)

- *Overall smartphone coverage bias* in many substantive estimates relatively small; especially once adjusting for sociodemographic differences between general population and smartphone owners
    - High social inclusion: +2.8 p.p.
    - Size of personal network: n.s.
- Comparable *Android smartphone coverage bias* after sociodemographic adjustment
    - High social inclusion: +1.6 p.p.
    - Size of personal network: n.s.
- Much larger *iPhone coverage bias*, even after adjusting for sociodemographics (up to 11 p.p.)

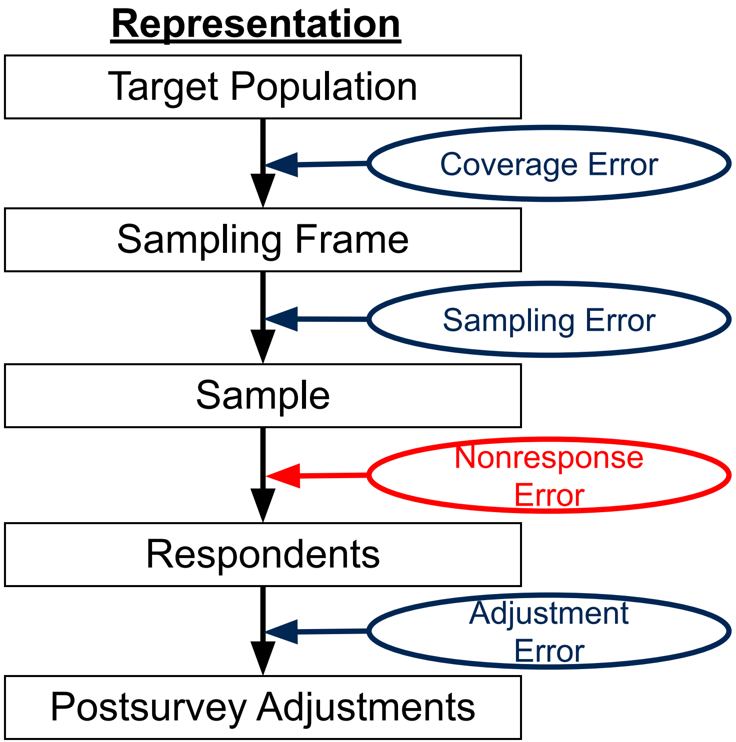
Solution to coverage problem: Providing (loaner) smartphones

- Providing participants with device for time of field period seems standard procedure for studies with older populations (e.g., Compernolle et al. 2022; English et al. 2022; Fingerman et al. 2020, 2022; Fritz et al. 2017; Huo et al. 2020; Maher et al. 2018; York Cornwell & Cagney 2017, 2020)

- Pros
  - Increasing coverage
  - Standardizing measurement (e.g., iOS vs. Android)
  - Use specifically configured devices

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

Representation error in smartphone data collection

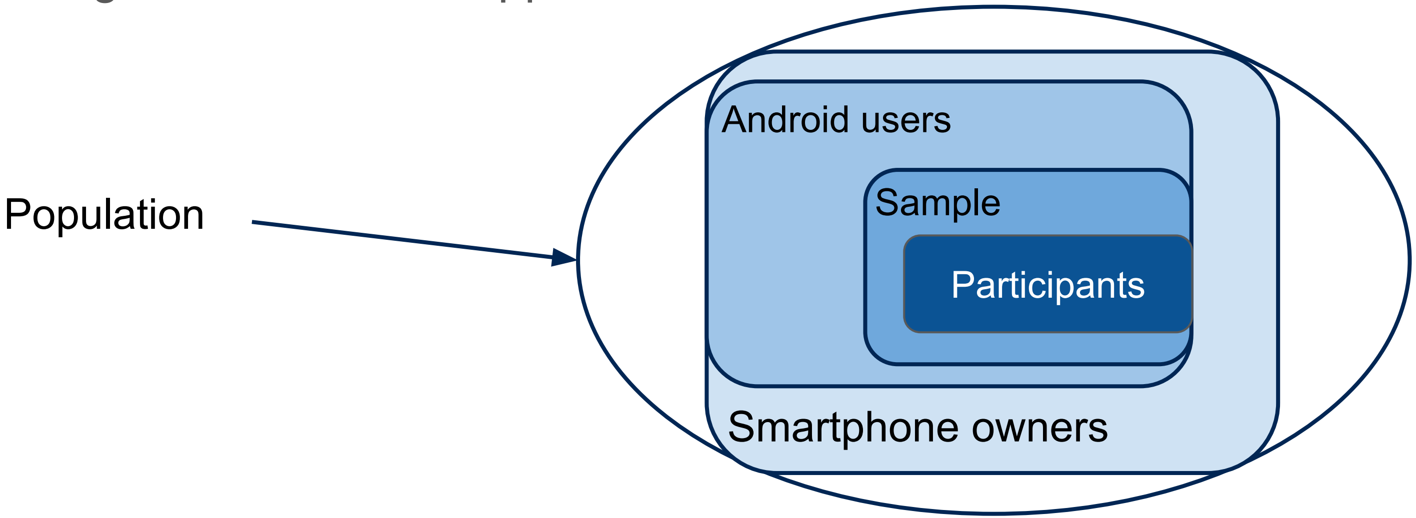


- **Nonparticipation error:** Individuals with higher privacy concerns are less likely to consent to sharing GPS data.

To participate in a smartphone study, one needs to…

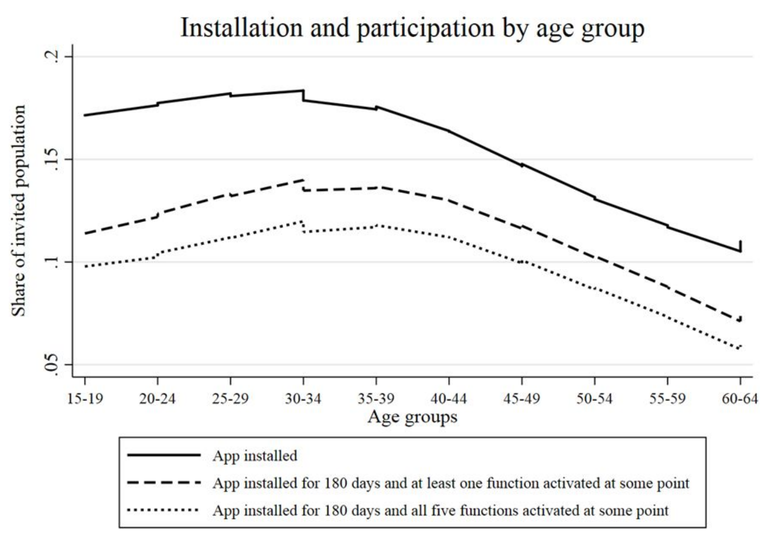
- …have access to a (specific) smartphone → (potential) Coverage error
- …be able to download an app
- …be willing to download an app

(potential) Nonparticipation error



Age as strong predictor of participation in general population studies

- *UK Understanding Society IP Budget App* for receipt scanning (Jäckle et al. 2019)
  - 51-60: -2.6 p.p.
  - 61-70: -5.7 p.p.
  - 71+: -2.2 p.p.
- Dutch *CBS Travel App* study with GPS (McCool et al. 2021)
  - under 50: >40%
  - 50-69: 34%
  - 70+: 16%
- *IAB-SMART* with 5 passive data collection functions (Keusch et al. 2022) ⟶



Other correlates of non-participation

- Willingness to participate
  - Privacy concerns (Keusch et al. 2019; Revilla et al. 2019; Struminskaya et al. 2020; Wenz et al. 2019)
  - Smartphone skills and smartphone activities (Keusch et al. 2019; Struminskaya et al. 2020, 2021; Wenz et al. 2019)
- Actual participation
  - Education (Jäckle et al. 2019; Keusch et al. 2021, 2022; McCool et al. 2021)
  - Reading proficiency (Keusch et al. 2021)
  - Income (McCool et al. 2021)
  - Panel tenure (Keusch, Bähr et al. 2022)
- Nonparticipation bias in substantive variables
  - Size of personal network and use of social media (Keusch, Bähr et al. 2022)
  - Time use (Elevelt et al. 2019)
  - Financial behavior (Jäckle et al. 2019)

Two major reasons for non-participation reported

- Privacy/security concerns and lack of skills

Table 3
Reasons for not participating in the app study

	N	% of cases
Did not have time to scan	168	39.6
Did not try to download the app	126	29.7
Not willing to share spending information	84	19.8
Not confident using my phone or tablet for this kind of activity	75	17.7
Not able or confident to download apps onto my phone or tablet	66	15.6
Do not have a smartphone or tablet which can download apps	60	14.2
Not confident that information would be held securely	60	14.2
Not interested	47	11.1
Did not have sufficient storage space to download the app	40	9.4
Do not have access to the internet on my phone or tablet	23	5.4
Could not download the app because not compatible with operating system	18	4.3
Link to downloading the app did not work	13	3.1
Could not find the app in the app store	8	1.9

n = 425. Multiple mentions

Jäckle et al. (2019)

Table 3. Reasons for and against participation in passive mobile data collection (n = 1,947)

Reasons for not participating		Reasons for participating	
Privacy, data security concerns	44%	Interest, curiosity	39%
No incentive; incentive too low	17%	Incentive	26%
Not enough information/control of what happens with data	12%	Help research, researcher	18%
Do not download apps	7%	Trust, seems legitimate, safe	11%
Not interested, no benefit	6%	Will help create better products & services	7%
Not enough time, study too long	5%	No additional burden	6%
Do not use smartphone enough; not right person for this study	5%	Like surveys & research	4%
Not enough storage	1%	Fun	3%
Other reasons	6%	Other reasons	4%
NA	3%	NA	2%

NOTE.—Percentages do not add up to 100 because respondents could mention multiple reasons.

Keusch et al. (2019)

Some learnings from earlier smartphone studies with older adults to secure participation

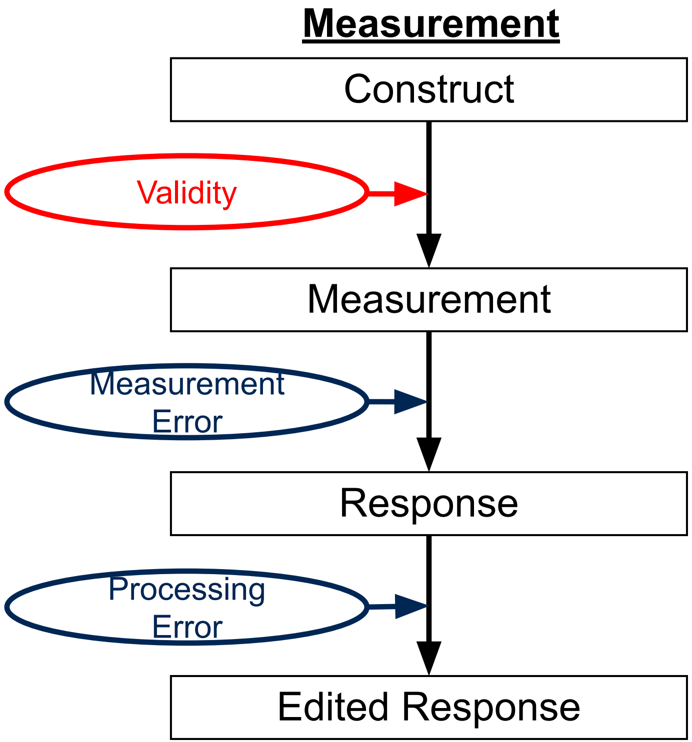
- In-person recruitment (e.g., in community or senior centers) seems to be well-working standard (Fritz et al. 2017; Maher et al. 2018; York Cornwell & Cagney 2017, 2020)
- Telephone recruitment can work but needs in-person follow-up (Fingerman et al. 2019, 2022; Hou et al. 2020)
- In-person consent, set-up, and training necessity
- Incentives should be provided for study enrollment AND any additional tasks
    - $50 for interview and $100 for EMAs, recordings, and photos (Fingerman et al. 2019, 2022; Hou et al. 2020)
    - $80 for at least 80% of all EMAs (Maher et al. 2018)

Potential measures to increase study compliance among older participants

- Additional technical support throughout field period
- Vibrate AND sound for EMA pinging
- Pouch to wear smartphone throughout day
- Daily reminder calls to charge device

Based on experience from the *Daily Experiences and Well-being Study* (personal communication with Heidi Guyer)

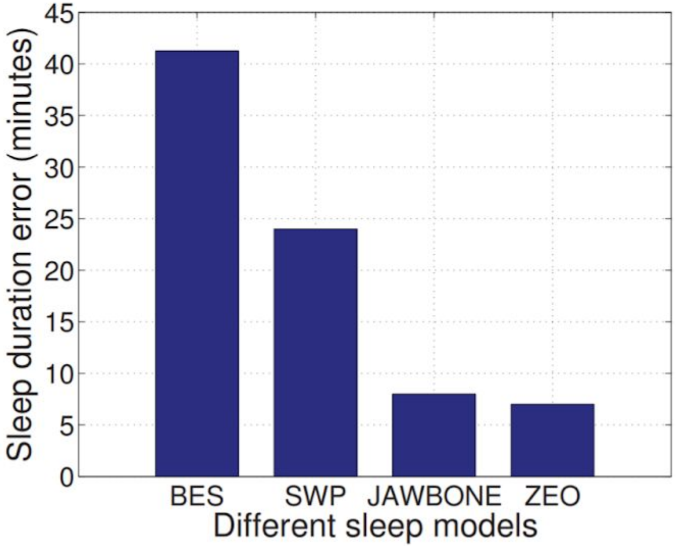
Measurement error in smartphone data collection



- **Validity:** You are using actigraphy to detect intensity of physical activity in a sample of older adults. Your study population is very sedentary and it is difficult to identify physical activity versus usual activity.

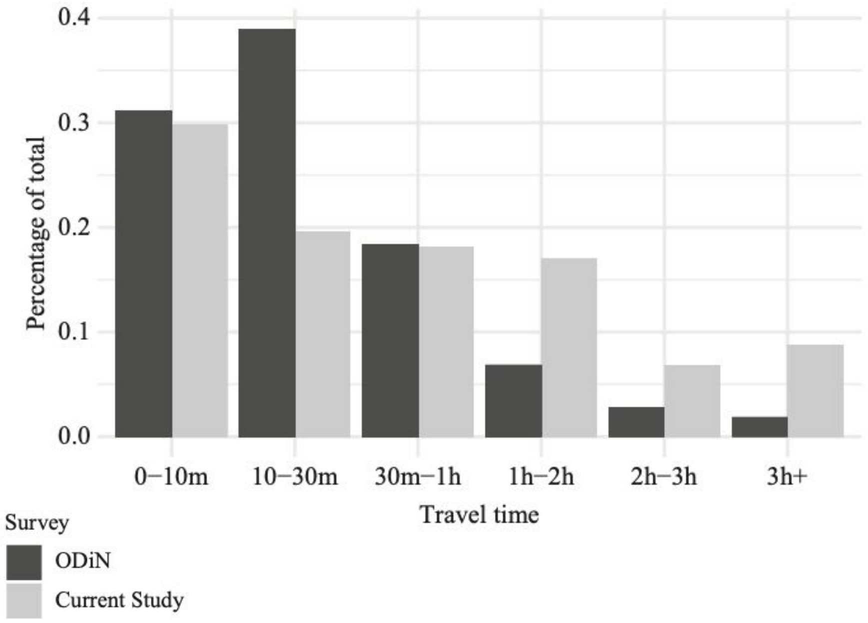
Researchers must often infer behavior from pattern of sensor data

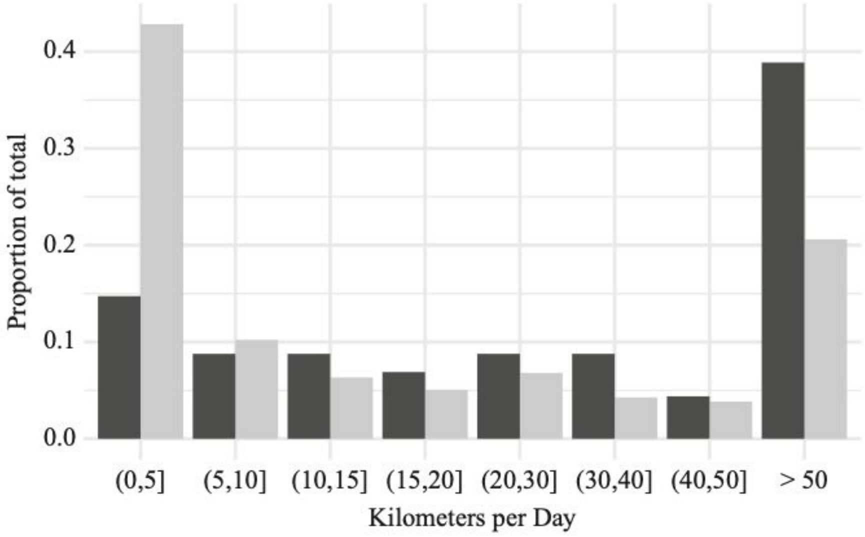
- Does absence of light, sound, and activity measured by a smartphone equal sleep?



Chen et al. (2013)

For some measures, smartphone sensors seem to be provide highly valid data





McCool et al. (2021)

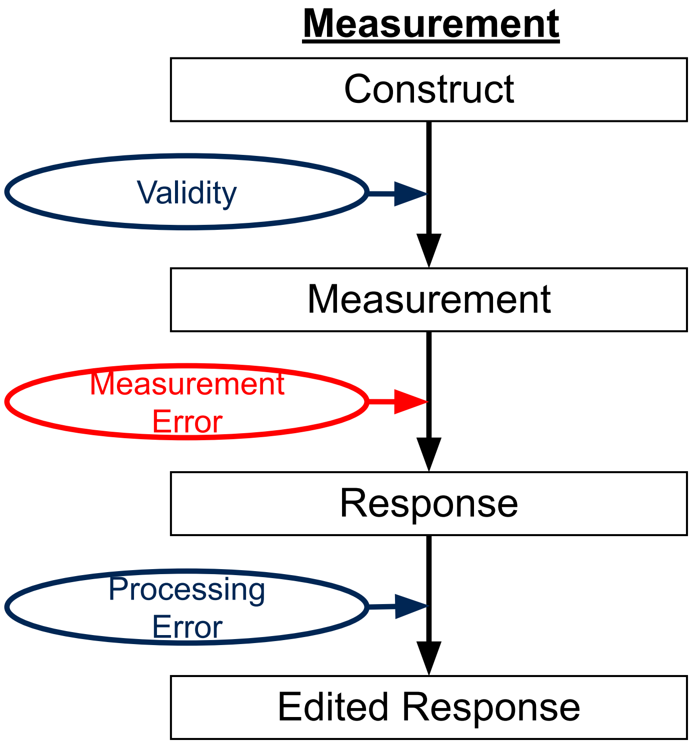
Whether smartphones measures are valid also depends on how individuals use device

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

Note: *...likelihood of behavior significantly increases with age

Keusch, Wenz, & Conrad (2022)

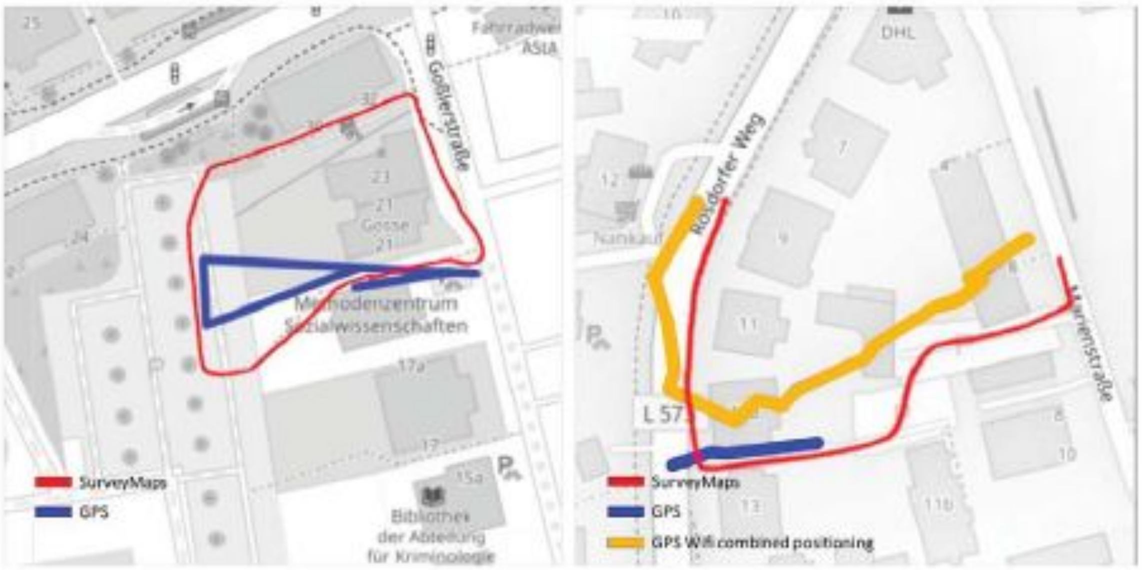
Measurement error in smartphone data collection



- **Measurement error:** GPS is less precise in urban areas where there are many large buildings.

Errors during data collection

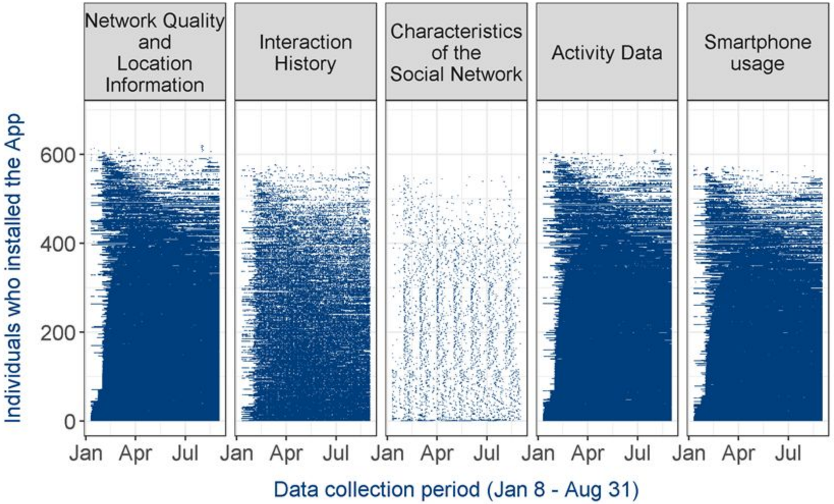
- Sensor-based errors/differences
  - Differences between types of sensors as well as brands and models of devices
  - Not one sensor/device per se better than others, depends on what should be measured under what circumstances



Schlosser et al. (2019)

Errors during data collection

- Sensor-based errors
- 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
    - …



Bähr et al. (2022)

Errors during data collection

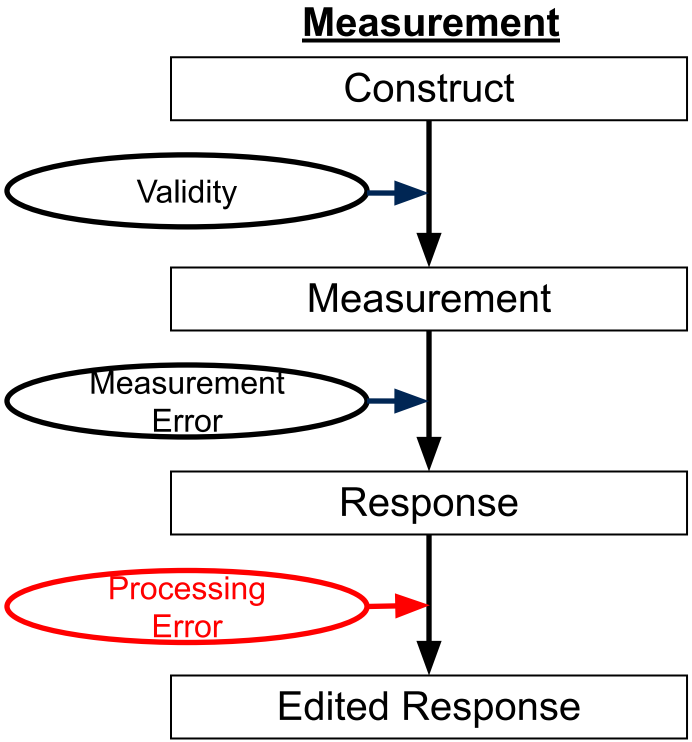
- Sensor-based errors
- Missing data
- Erroneous/Invalid data
  - e.g., fake GPS apps, VPN

Errors during data collection

- Sensor-based errors
- Missing data
- Erroneous 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) (Kapteyn et al. 2021)

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

Measurement error in app, sensor & wearables data collection



- **Processing error:** Raw accelerometer data are classified as different types of activity based on training data.

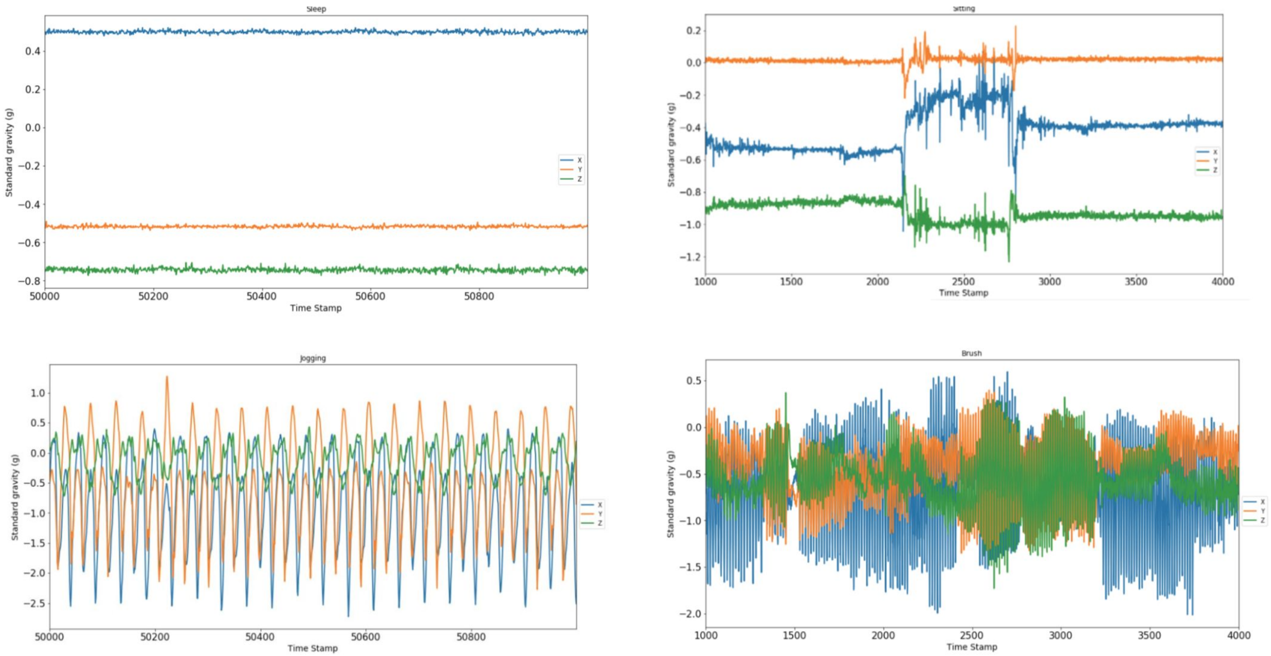
Errors during processing raw data

- Raw sensor data must be processed and classified to infer behavior
  - Processing on user’s device using (built-in) third party or researcher-developed algorithm
    - Preserves storage and protects privacy
    - No access to raw data
  - Researcher’s server
    - Full control over data processing
    - All data needs to be transfered
- “Black box” approach when using third-party algorithm to classify data on device
  - Activity classification was trained based on data from young adults (“WEIRDOS” ©Mick P. Couper) → used to classify behavior of older adults

Source: Kapteyn et al. (2019)

Example: Detecting types of activity

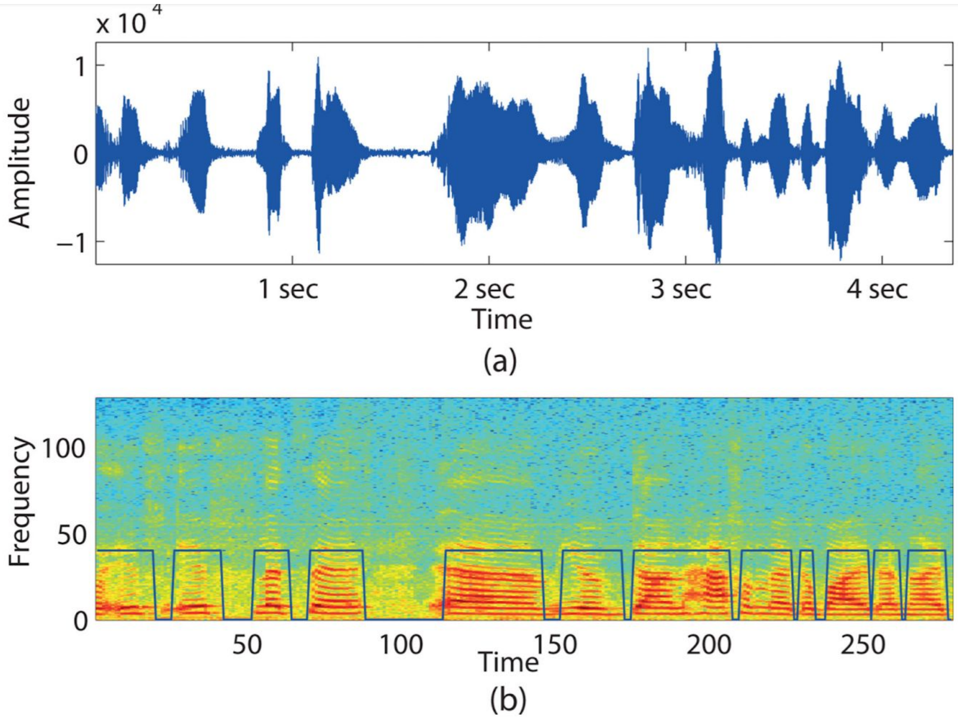
- Patterns in raw data have to be classified as activities



Mulder et al. (2019)

Example: Detecting conversations

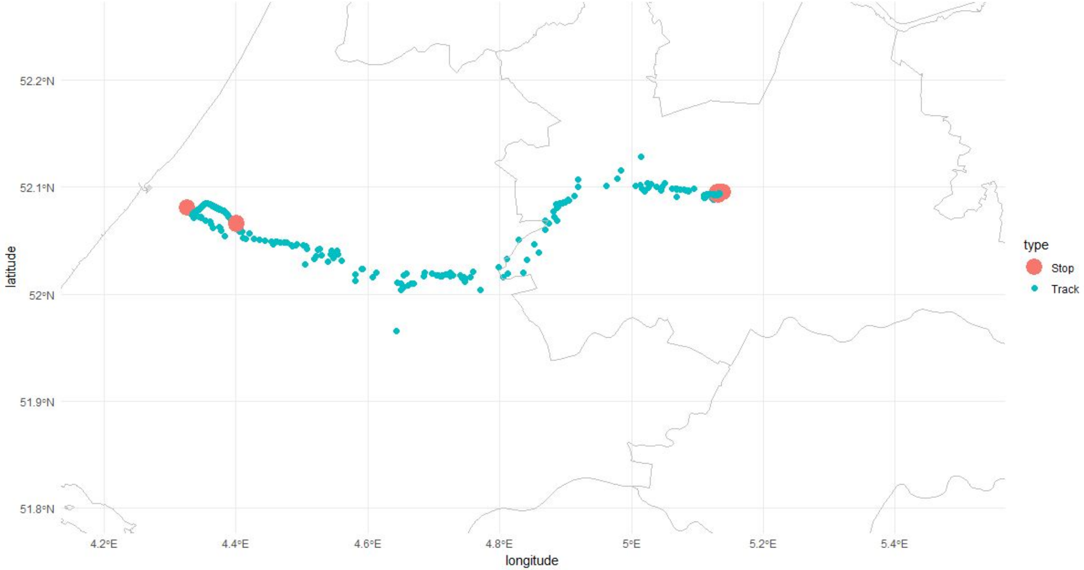
- Using smartphone microphone to detect personal conversations
  - Microphone always on but content of conversation not transmitted
  - Outcome of inference: 0 = no conversation, 1 = conversation
- Processing raw data on device
  - Privacy sensitive classifiers
  - Transferred data only includes aggregated information

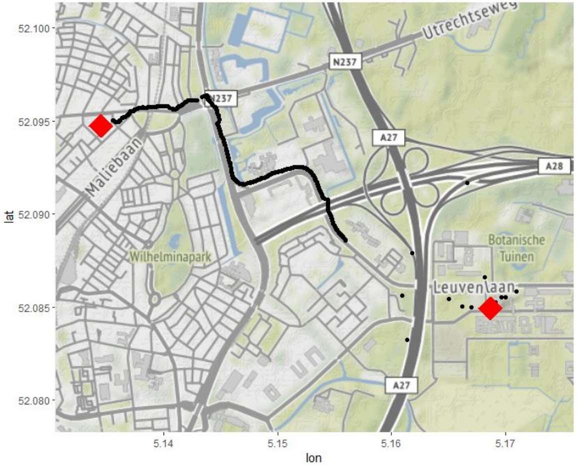


Rabbi et al. (2011)

Example: GPS tracks and stop detection

- Stops defined based on “static” location: radius has to be (pre)defined by researcher





McCool et al. (2019)

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

Our own book…

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

Questions

Thank you!

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

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