Utrecht University

Designed big data

Survey Data Analysis 2022

Bella Struminskaya & Peter Lugtig

b.struminskaya@uu.nl http://bellastrum.com/

Outline

- Non-probability inference competition

- Some benefits of big data for inference
  - Often non-probability
- Mixing surveys and big data
  - Calibration
  - Designed big data
- Data donation and willingness (Bella Struninskaya)

Results last weeks’ competition

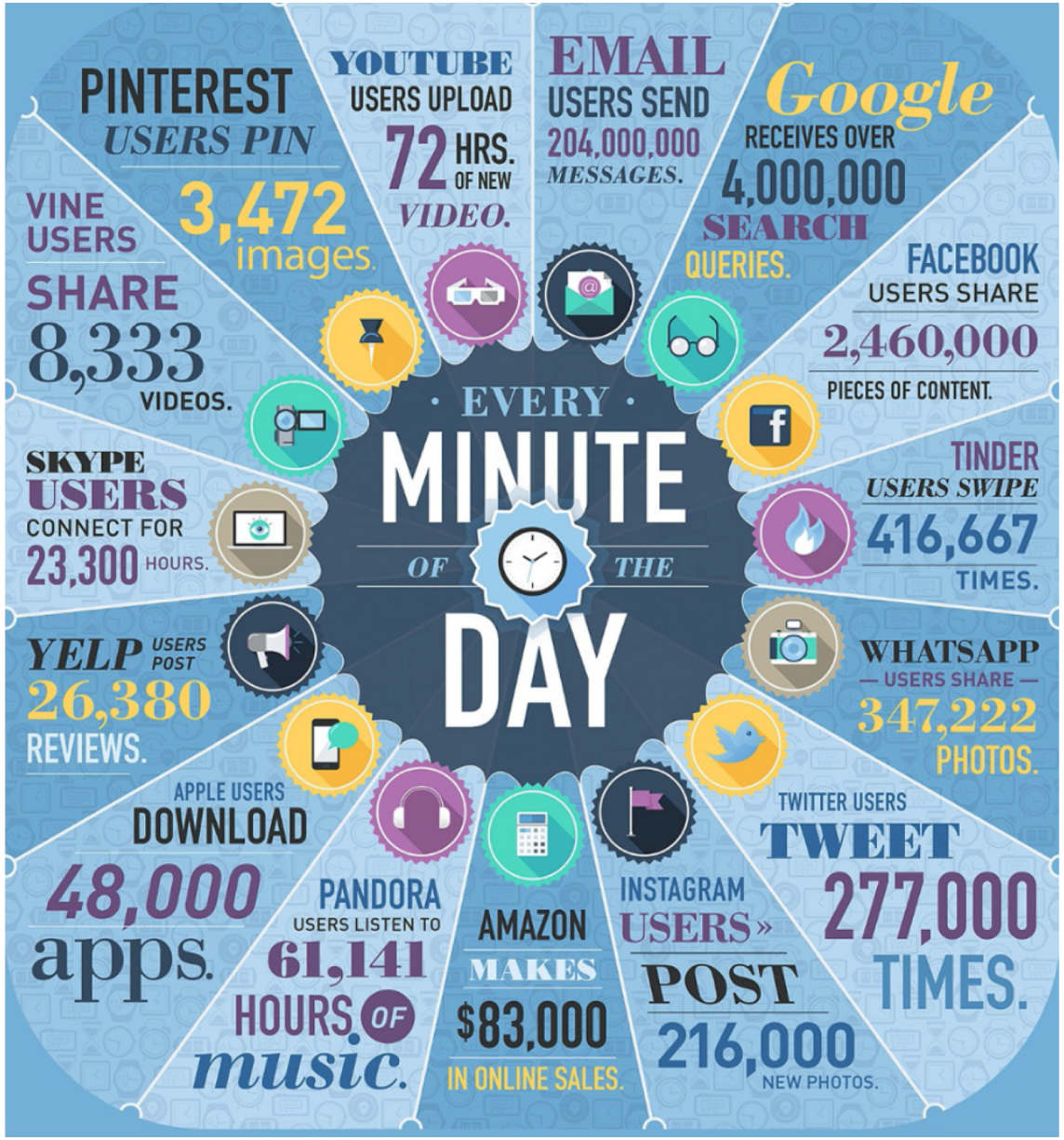
Organic / big / found data sources:

Very often non-probability
(see eg. Meng, 2018)

1) *Transaction data*: describe an event, e.g., a person interacts with a business or a government entity

2) *Social media data*: scraped from social networks, blogs, web searches etc. E.g., Google Flu Trends

3) *Internet of Things (IoT) data*: data collected from interconnected devices such as autos, household appliances, security cameras, wearable sensors, GPS locators etc. E.g., gathering data on movement of people and things, electricity use (lifestyle & rhythms of daily life)



Characteristics of big data:

1) Volume
2) Variety ((no) structure)
3) Velocity
4) Veracity (accuracy)
5) Variability (differences in meanings across sources)
6) Value
7) Visualization

Source: Baker 2017, Infographic: James 2014

Types of big data

- Types of big data
  - **Administrative data** – provided by persons or organizations for regulatory or other government activities
  - **Transaction data** – generated as an automatic byproduct of transaction and activities (e.g., credit card data, traffic flow data)
  - **Social media data** – created by people with the express purpose of sharing with (some) others
  - **Sensor data** – GPS, accelerometers, heartbeat

Administrative data

- Statistics Netherlands
- Business administration
- Market data
- Pros
    1. Accuracy (?)
    2. Costs (?)
    3. Speed (?)
- Cons
    1. Missing data?
    2. Reliability: data collection and definitions the same?
    3. Validity:
        - Are they measuring what YOU want to measure?
        - Do you KNOW the definitions of variables? Are they yours?

Transaction data

-Data Availability? Often proprietary! A key strength of surveys is public access to data, permitting **replication and reanalysis**
-Not everyone uses cards!
-Knowing what people buy is not the same as understanding WHY they buy!

Social Media Data

- Selection bias: “haves” versus “have-nots”
  - Not everyone uses social media!
  - Need to distinguish between producers and users of users of social media – small part of online population actively tweets
- Measurement bias
  - Self-presentation bias: Impression management is a key element of social media
  - The average Facebook user has MANY “friends”

Sensor data

-Not everyone allows you to track them: 47% share their GPS coordinates (Struminskaya et al. 2018)
-some type of activities are difficult to measure
-thresholds for intensity are arbitrary

Surveys & Big data

• "Designed" data: Collected for the research purposes • Researcher control over content • Large number of covariates • Detailed documentation of the data generating process	• "Organic" data: Collected for purposes other than research • No control over content • Limited number of covariates • No / little documentation • Access issues • (Missingness & coverage)
• High nonresponse • Small N • Measurement error (recall, social desirability)	• Large N • No measurement error due to self-report

(based on Baker 2018, Groves 2011, Sakshaug 2015, Salganik 2018)

Can anonymized data from mobile phone networks predict poverty and wealth?

- Anonymized call records (1.5 mil)
- Telephone survey (n=856)

ECONOMICS

Predicting poverty and wealth from mobile phone metadata

Joshua Blumenstock,[1]* Gabriel Cadamuro,[2] Robert On[3]

Accurate and timely estimates of population characteristics are a critical input to social and economic research and policy. In industrialized economies, novel sources of data are enabling new approaches to demographic profiling, but in developing countries, fewer sources of big data exist. We show that an individual's past history of mobile phone use can be used to infer his or her socioeconomic status. Furthermore, we demonstrate that the predicted attributes of millions of individuals can, in turn, accurately reconstruct the distribution of wealth of an entire nation or to infer the asset distribution of microregions composed of just a few households. In resource-constrained environments where censuses and household surveys are rare, this approach creates an option for gathering localized and timely information at a fraction of the cost of traditional methods.

Reliable, quantitative data on the economic characteristics of a country's population are essential for sound economic policy and research. The geographic distribution of poverty and wealth is used to make decisions about resource allocation and provides a foundation for the study of inequality and the determinants of economic growth (*1*, *2*). In developing countries, however, the scarcity of reliable quantitative data represents a major challenge to policy-makers and researchers. In much of Africa, for instance, national statistics on economic production may be off by as much as 50% (*3*). Spatially disaggregated data, which are necessary for small-area statistics and which are used by both the private and public sector, often do not exist (*4*, *5*).

In wealthy nations, novel sources of passively collected data are enabling new approaches to demographic modeling and measurement (*6*–*9*). Data from social media and the "Internet of Things," for instance, have been used to measure unemployment (*9*), electoral outcomes (*10*), and economic development (*8*). Although most comparable sources of big data are scarce in the world's poorest nations, mobile phones are a notable exception: They are used by 3.4 billion individuals worldwide and are becoming increasingly ubiquitous in developing regions (*11*).

Here we examine the extent to which anonymized data from mobile phone networks can be used to predict the poverty and wealth of individual subscribers, as well as to create high-resolution maps of the geographic distribution of wealth. That this may prove fruitful is motivated by the fact that mobile phone data capture rich information, not only on the frequency and timing of communication events (*12*) but also reflecting the intricate structure of an individual's social network (*13*, *14*), patterns of travel and location choice (*15*–*17*), and histories of consumption and expenditure. Regionally aggregated measures of phone penetration and use have also been shown to correlate with regionally aggregated population statistics from censuses and household surveys (*18*, *19*, *19*).

Our approach is different from prior work that has examined the relation between regional wealth and regional phone use, as we focus on understanding how the digital footprints of a single individual can be used to accurately predict that same individual's socioeconomic characteristics. This distinction is a scientific one, which also has several important implications: First, it allows for the method to be used in contexts for which recent census or household survey data are unavailable. Second, when an authoritative source of data does exist, it can be used to more objectively validate or refute the model's predictions. This limits the likelihood that the model is overfit on data from a single source, which is otherwise difficult to control, even with careful cross-validation (*20*). Third, our approach allows for a broad class of potential applications that require inferences about specific individuals instead of census tracts. As we discuss in the supplementary materials (section 6), future iterations of this approach could help to improve the targeting of humanitarian aid and social welfare, disseminate information to vulnerable populations, and measure the effects of policy interventions.

For this study, we used an anonymized database containing records of billions of interactions on Rwanda's largest mobile phone network and supplemented this with follow-up phone surveys of a geographically stratified random sample of 856 individual subscribers. Upon contacting and surveying each of these individuals, we received informed consent to merge their survey responses with the mobile phone transaction database. The surveys solicited no personally identifying information but contained questions on asset ownership, housing characteristics, and several other basic welfare indicators. From these data, we constructed a composite wealth index using the first principal component of several survey responses related to wealth (*21*, *22*) (supplementary materials section 1D). For each of the 856 respondents, we thus have ~75 survey responses, as well as the historical records of thousands of phone-based interactions such as calls and text messages (Table 1).

We use the merged data from this sample of 856 phone survey respondents to show that a mobile phone subscriber's wealth can be predicted from his or her historical patterns of phone use (Fig. 1A) (cross-validated correlation coefficient $r = 0.68$). Our approach to modeling combines feature engineering with feature selection by first transforming each person's mobile phone transaction logs into a large set of quantitative metrics and then winnowing out metrics

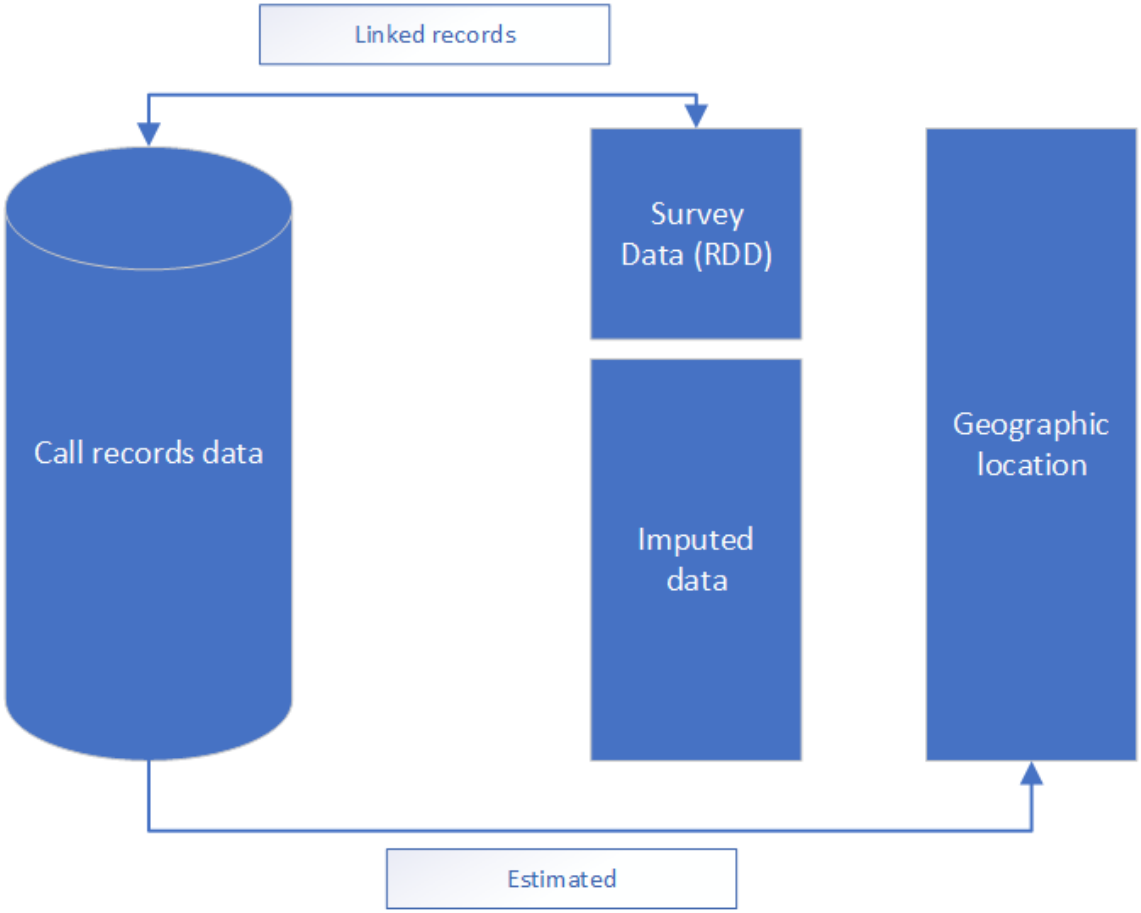
[1]Information School, University of Washington, Seattle, WA 98195, USA. [2]Department of Computer Science and Engineering, University of Washington, Seattle, WA 98195, USA. [3]School of Information, University of California, Berkeley, Berkeley, CA 94720, USA.
*Corresponding author. E-mail: joshblum@uw.edu

Table 1. Summary statistics for primary data sets. Phone survey data were collected by the authors in Kigali, in collaboration with the Kigali Institute of Science and Technology. Call detail records were collected by the primary mobile phone operator in Rwanda at the time of the phone survey. Demographic and Health Survey (DHS) data were collected by the Rwandan National Institute of Statistics. N/A, not applicable.

Summary statistic	Phone survey	Call detail records	DHS (2007)	DHS (2010)
Number of unique individuals	856	1.5 million	7377	12,792
Data collection period	July 2009	May 2008–May 2009	Dec. 2007–Apr. 2008	Sept. 2010–Mar. 2011
Number of questions in survey	75	N/A	1615	3396
Primary geographic units	30 districts	30 districts	30 districts	30 districts
Secondary geographic units	300 cell towers	300 cell towers	247 clusters	492 clusters

(Blumenstock et al. 2015)

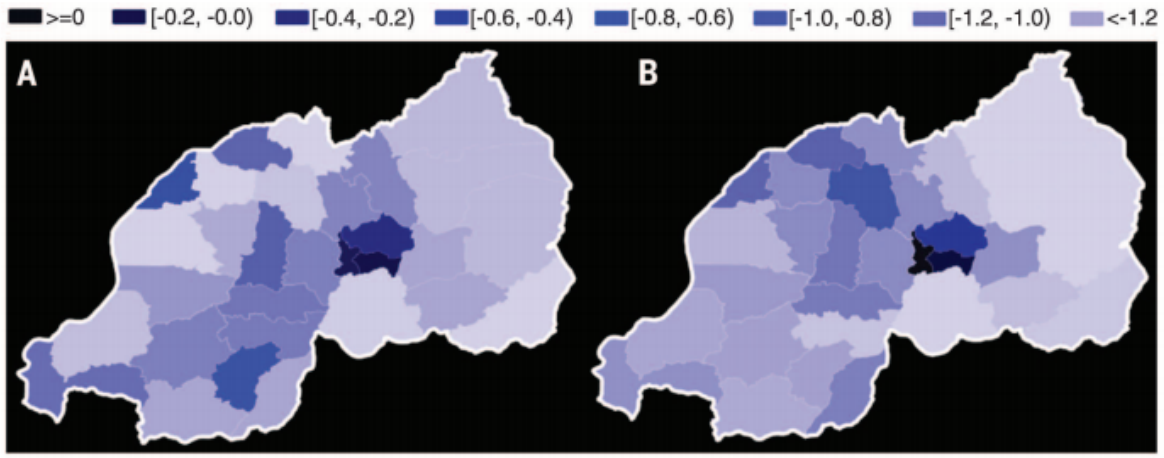
Can anonymized data from mobile phone networks predict poverty and wealth?



- Call activity
- SMS activity
- International communications
- Network structure
- Movement
- etc.

Can anonymized data from mobile phone networks predict poverty and wealth?

- Anonymized call records (1.5 mil)
- Telephone survey (n=856)
- ‘Gold standard’ f2f Demographic and Health Survey (n=12792)

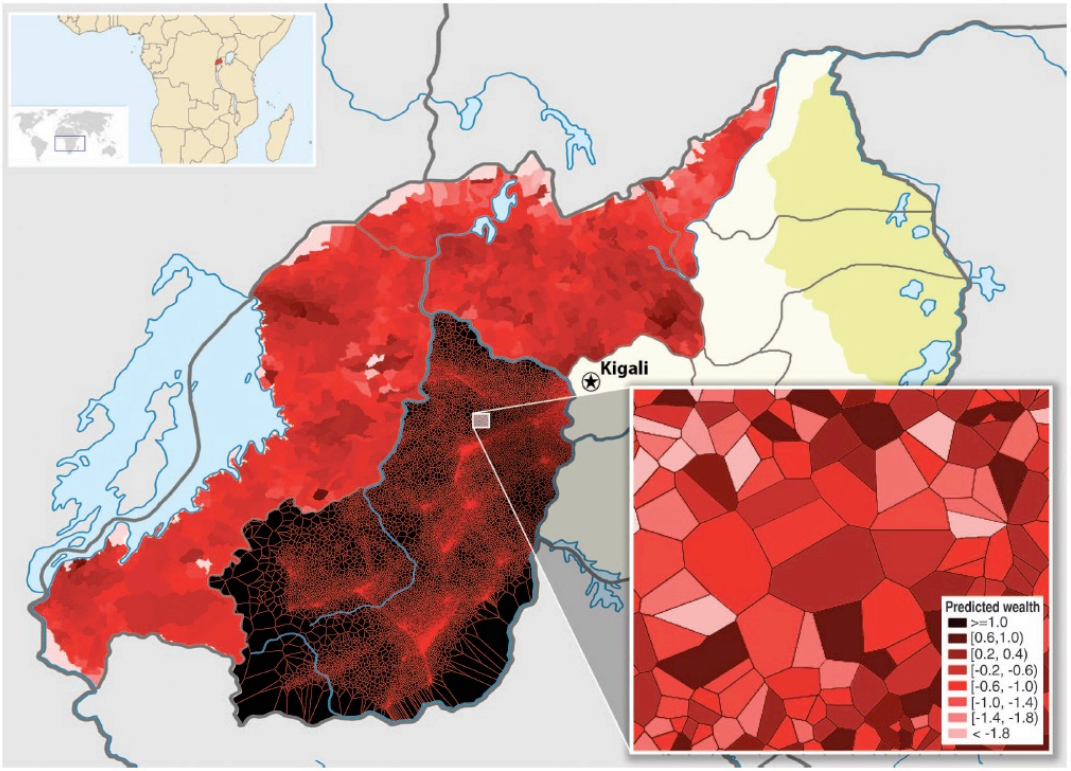


Composite wealth index: A – predicted from call data, B – actual from DHS, r=0.79

(Blumenstock et al. 2015)

Added value

- High-resolution maps of poverty and wealth
- Small area estimation: survey provided estimates on cluster level, call records much richer
- Timely data
- Costs (12,000 vs. 1 Mil)

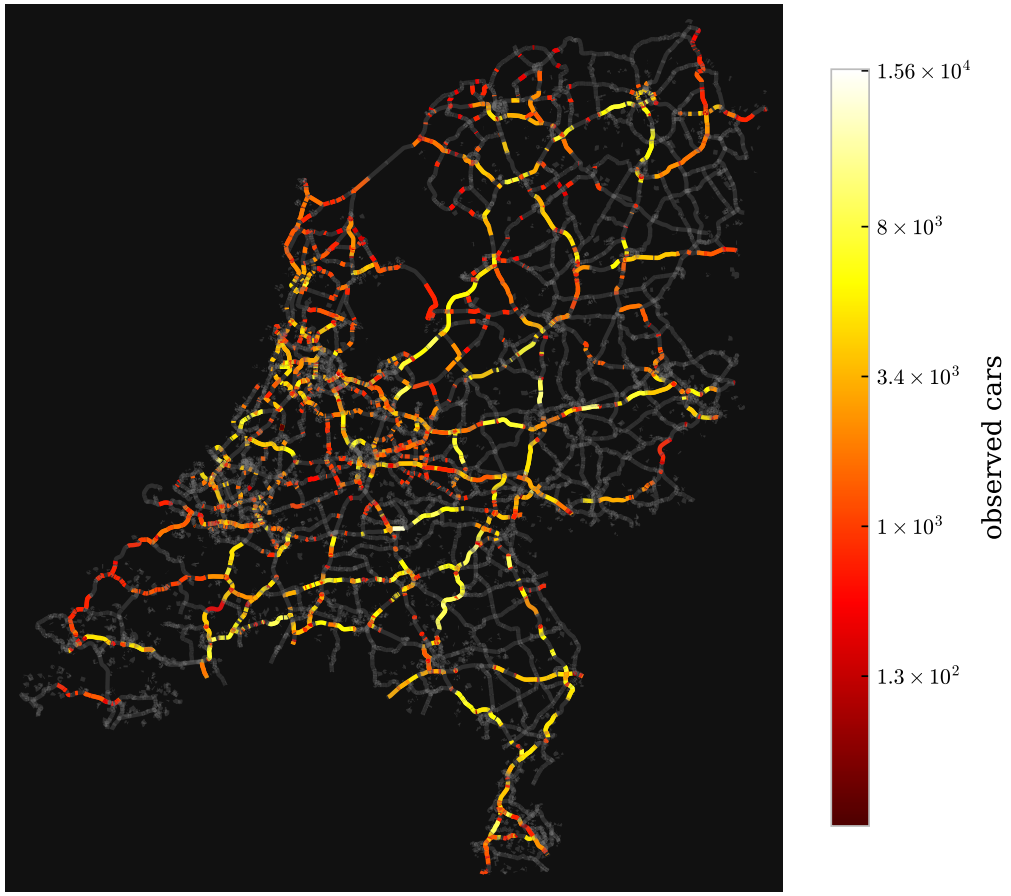


Bostanci et al (2022) – source 1 :traffic sensors

Traffic sensors on Dutch roads
Number of cars/trucks passing by every minute
- 1440 measurements by day

Continuous data

Problem:
- Lots of roads are missing



Bostanci –source 2 (admin data)

Uses admin data by CBS

~ 8 million people who have a job

1. Home and work address
2. Use trip planner to predict
   a) Likelihood of traveling by car
   b) Route traveled
3. Predict traffic intensity

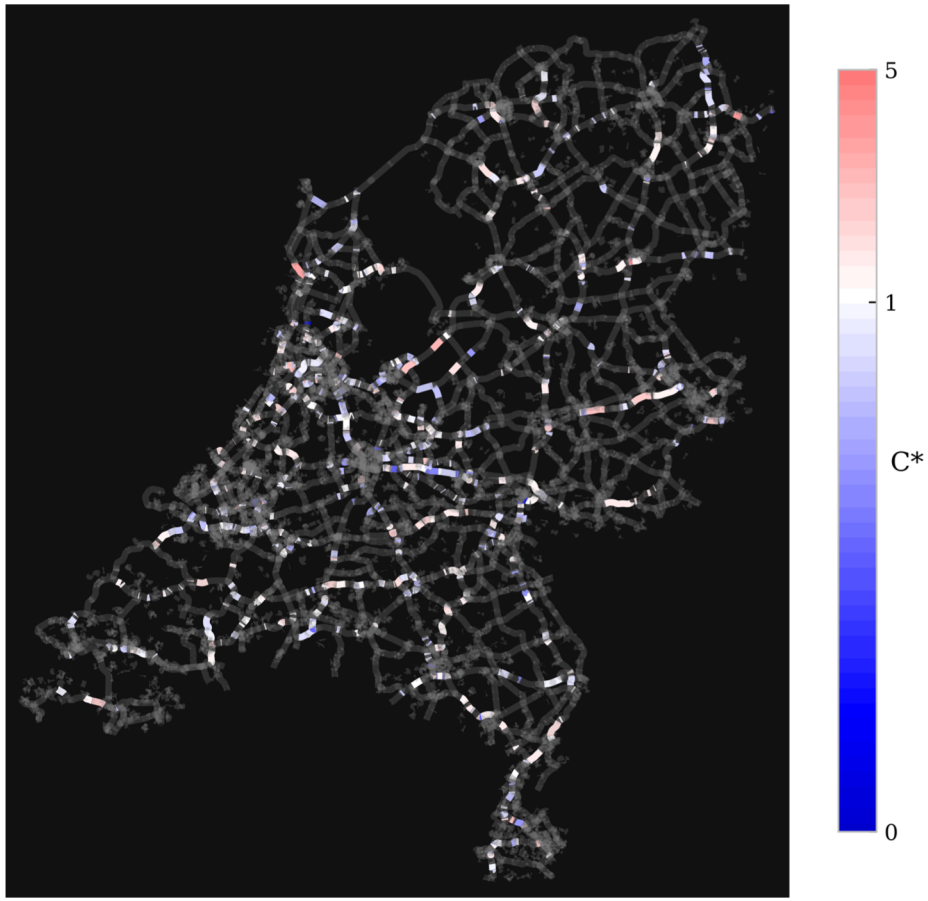
Problem: are these data accurate?

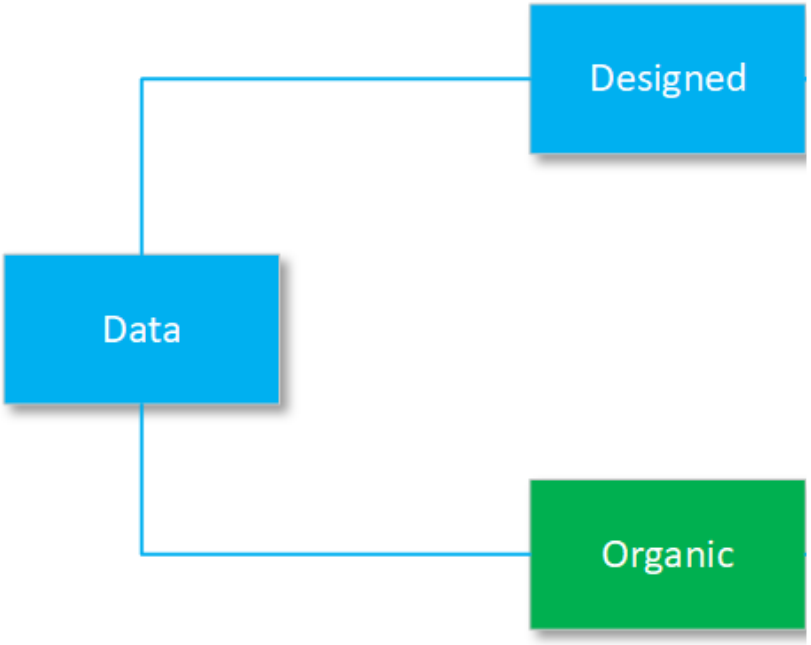
Bostanci – compare sources

Red: overestination in sensors
Blue: overestimation in admin data

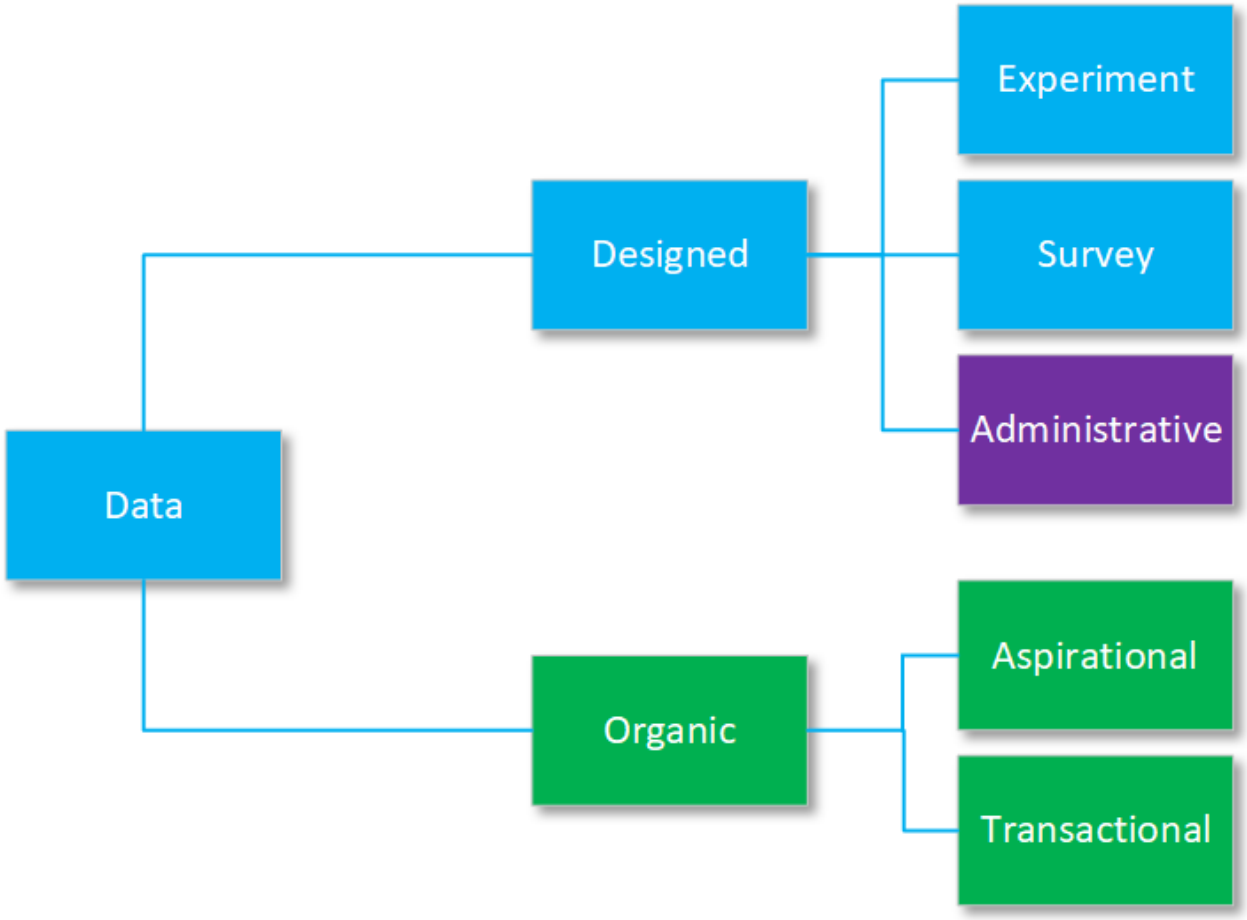
Model does pretty well!

- Allows us to identify problems in admin data
- And to predict road traffic intensity for all roads in Netherlands





(Source: Kreuter 2018)



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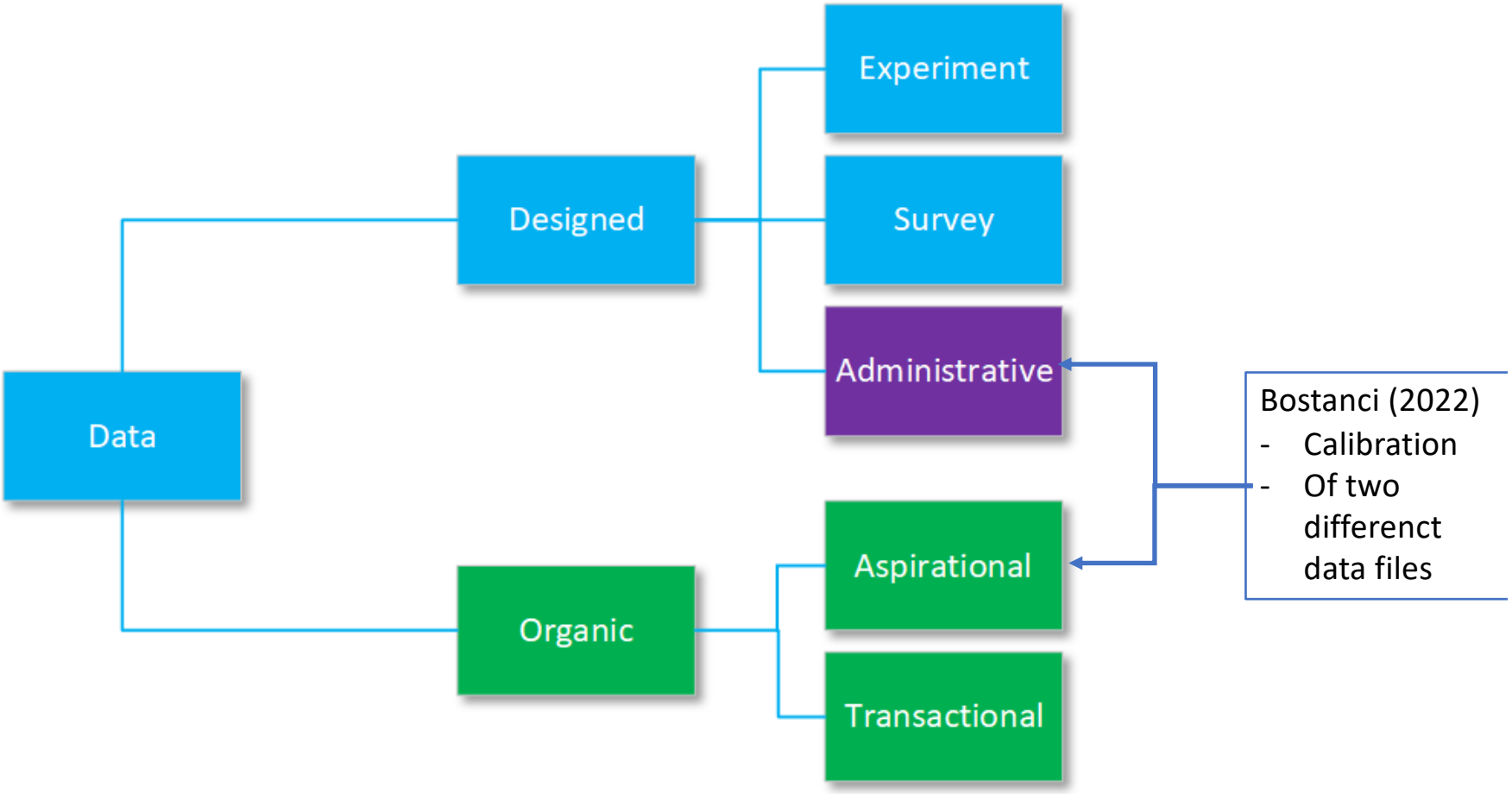


(Source: Kreuter 2018)

Coverage in Big Data

- Does the sampling frame include all units of the population?

	High coverage?	Difference frame /population	Adjustment possible
Administrative data	yes, except for people that are not registered, e.g. illegals, homeless	++	Via snowball sample
Transaction data	Only those that pay with cards	+	Cash survey/observation
Social media data	Only those that are on social media	-	General population survey
Sensor data	Only those that wear sensors and allow you to track them	-	Nonresponse survey

Sampling in Big Data

- No differences between big data and survey data
- Is sampling necessary?
  - Often no additional costs for using census instead of sample
- Often the unit of observation is not the individual
  - Transaction with transaction data
  - Verbal comment with social media data
  - Data capture point with sensor data
    - Recode into individual data
    - Dependent observations (many observations from few individuals)

Administrative data	++
Transaction data	+
Social media data	--
Sensor data	--

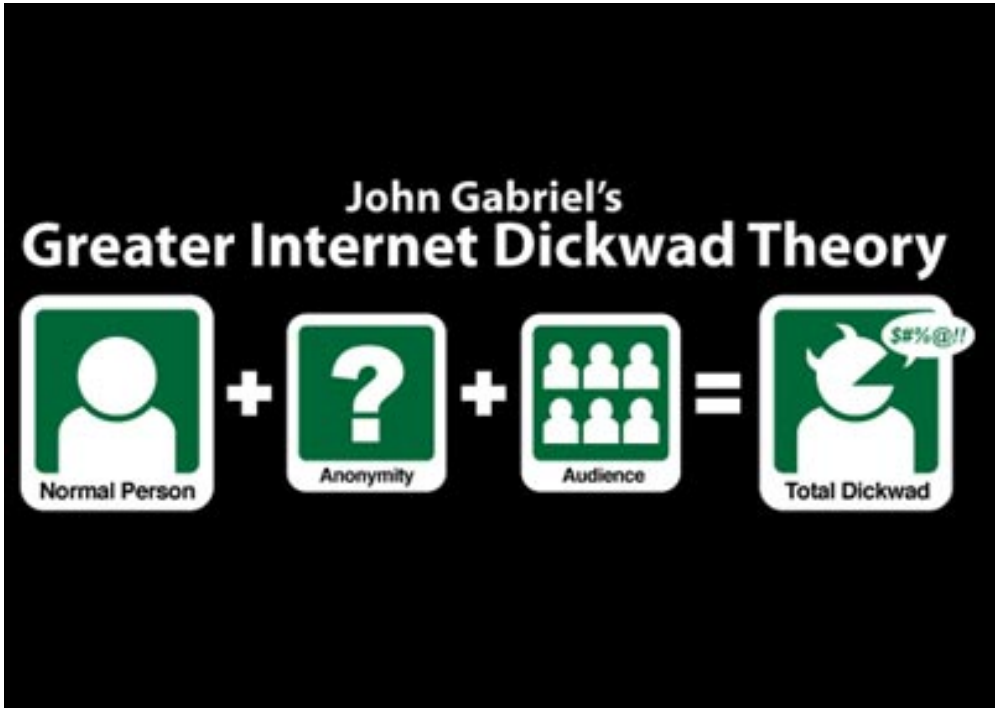
Nonresponse in Big Data

- Sampled but not collected
- In principle, there is no non response in big data
- Nonresponse error/bias is an important issue in surveys
- Check
  - Compare big data to external data
  - Investigate internal variation within the data, e.g. difference in estimates by the number of verbal comments in social media data
  - Examination of adjustment estimates, where each adjustment contains different assumptions about nonresponse

Administrative data	++
Transaction data	++
Social media data	-
Sensor data	--

Measurement in Big Data

- Is the data well-constructed, clear, and not leading or otherwise biasing? (AAPOR report survey quality, 2016)
- Do people provide truthful data?
- Were any respondents removed?



Measurement in Big Data

- Is the data well-constructed, clear, and not leading or otherwise biasing? (AAPOR report survey quality, 2016)
- Administrative data: do you know definitions? Are they the same as yours? Over time?
- Transaction data: accurate?!
- Social media data: Do people provide truthful data?
- Sensor data:
  - Objective weight is about 1 kilo lower than reported weight (Koorenman & Scherpenzeel, 2014)
  - Automatic trip detection with sensors (Geurs et al., 2015): inaccurate with small trips, public transport trips not classified, unsuccessful mode detection in 25% of trips

Administrative data	-
Transaction data	++
Social media data	--
Sensor data	-

Specification in Big Data

- Formulating and answering research questions
  - The construct implied in the data differs from the intended construct that should be measured (validity)
  - Problems of wording, context, concepts
  - Ask what is essential for the research question
- Check with qualitative techniques/interviews

Administrative data	**+/-**
Transaction data	+/-
Social media data	+/-
Sensor data	+/-

Costs in Big Data

- Big data is already out there, so little costs involved!

Administrative data	**++**
Transaction data	++
Social media data	++
Sensor data	+/-

Big data particularly useful for

- Replace surveys/most survey questions
  - Travel
  - Budget
  - User groups/online communities
- Increase survey data quality
  - Adding administrative data
  - Adding sensor data
  - Using social media data as a qualitative/pilot study
  - Transaction data? As an explanatory variable?

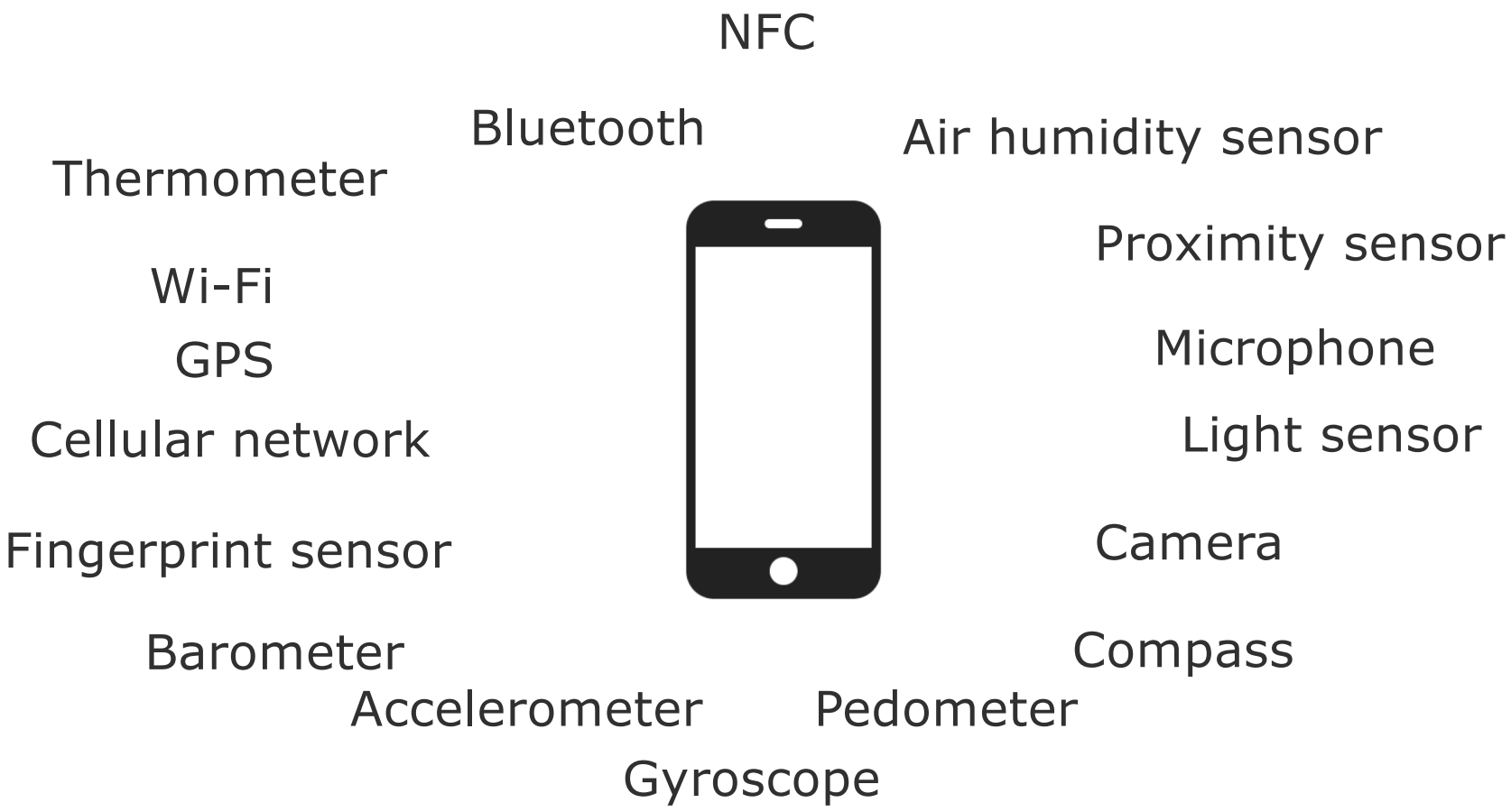
Passive data collection using smartphone sensors

Bella Struminskaya

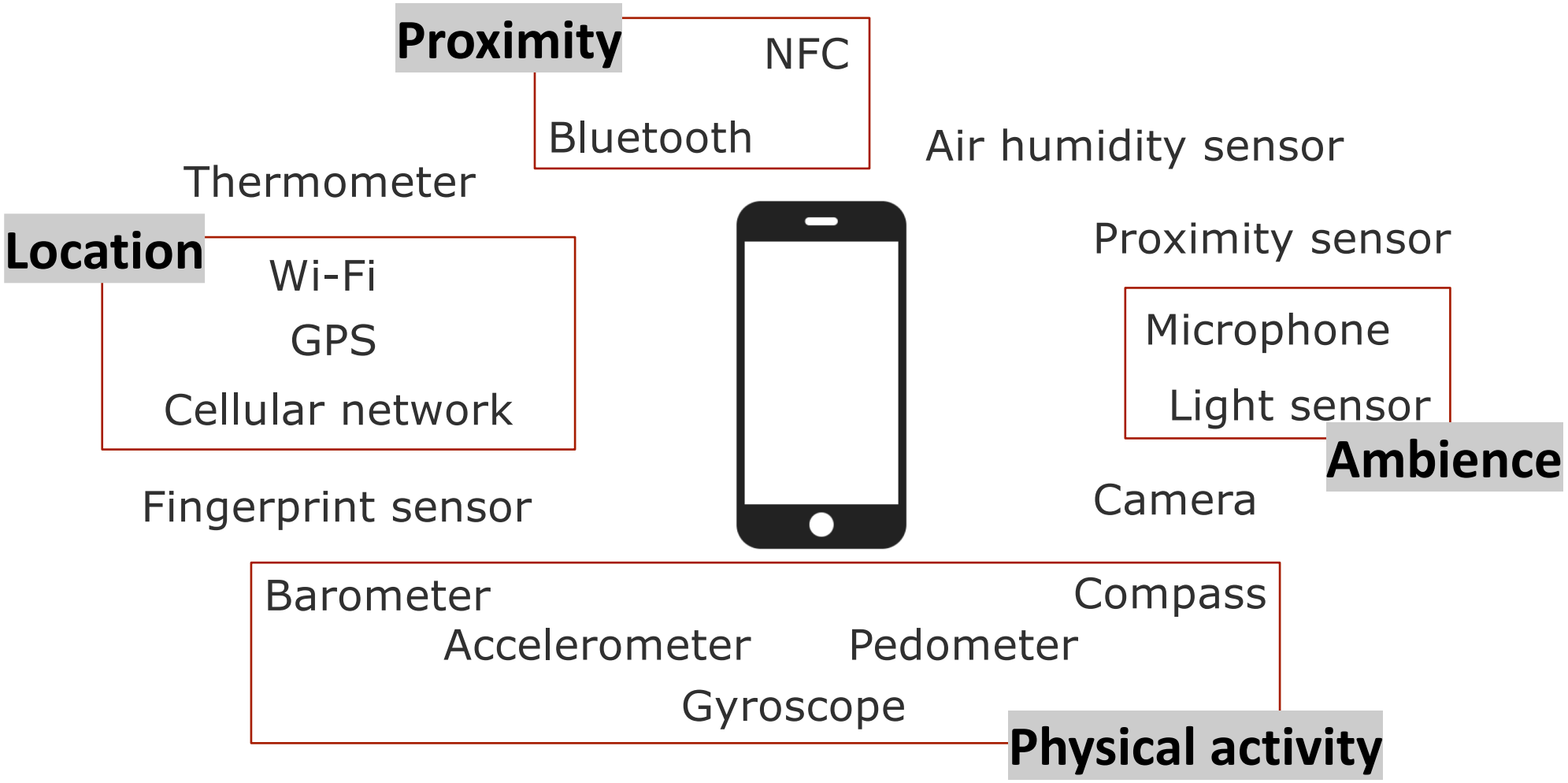
with thanks to Florian Keusch

b.struminskaya@uu.nl
http://bellastrum.com/

Native smartphone sensors

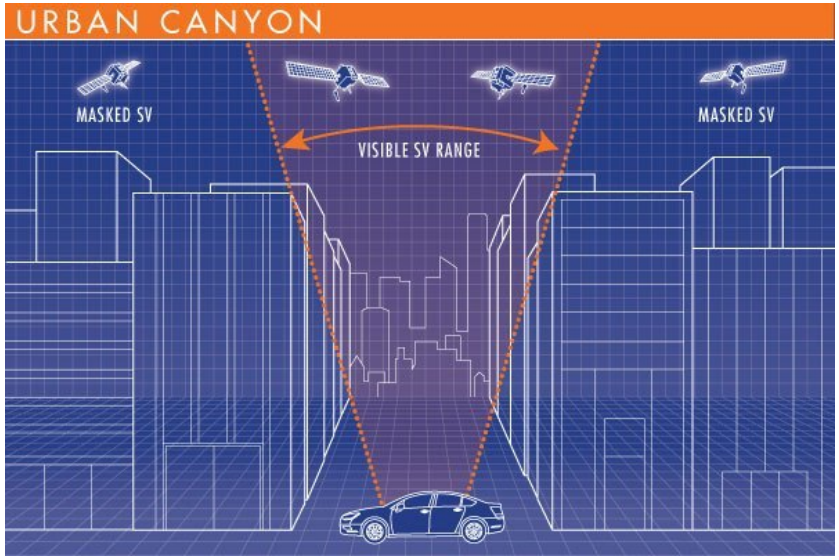


Native smartphone sensors



Location sensors

- GPS
  - Coordinates in longitude & latitude
  - High accuracy (newest generation 30 cm)
  - Works without cell/Internet connection
  - Performs worse in ‘urban canyons’, indoors, and underground (pseudo accuracy!)
  - Can be battery-draining
- Cellular network
  - Multilateration of radio signals between (several) cell towers
- WiFi
  - Inferring location from Wi-Fi access points (AP)
- Beacons
  - Bluetooth transmitters for indoors



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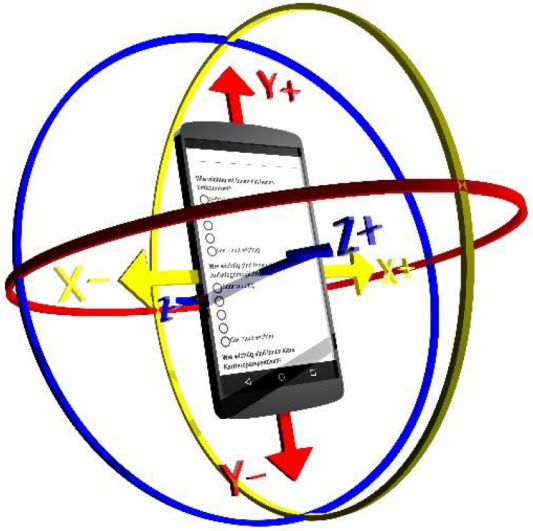
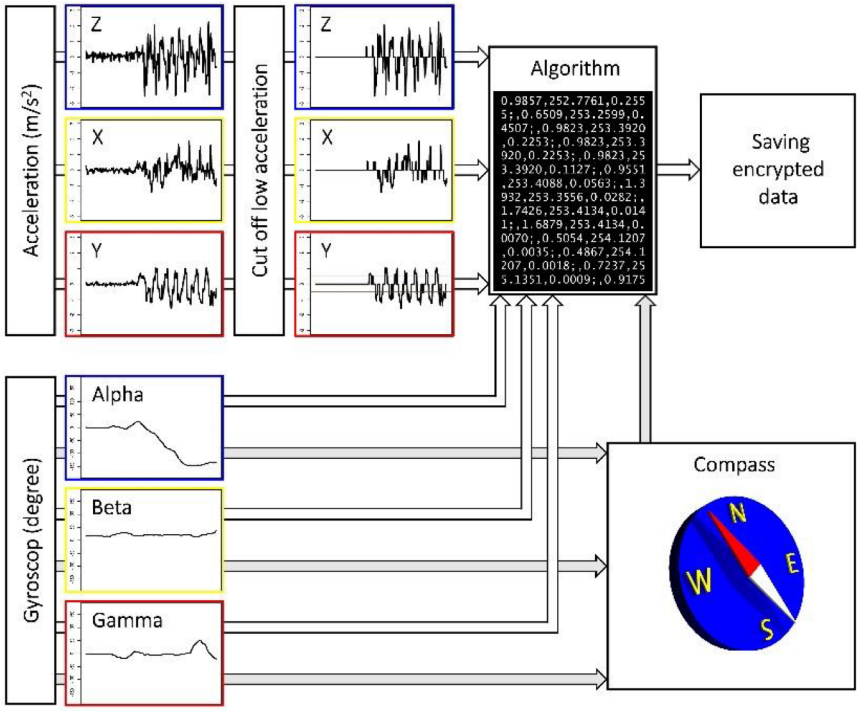
Physical activity sensors

- Accelerometer
- Gyroscope
- Mangnetometer
- Barometer
- Pedometer





Source: Schlosser et al. (2019)

Ambience sensors, proximity sensors

- Camera
  - photos, videos, scanning of bar codes
  - heart rate
  - linear distance
- Microphone
  - active and passive (ambient noise) recording
- Light sensor
  - e.g., identify idle state

- Bluetooth
- RFID
- NFC

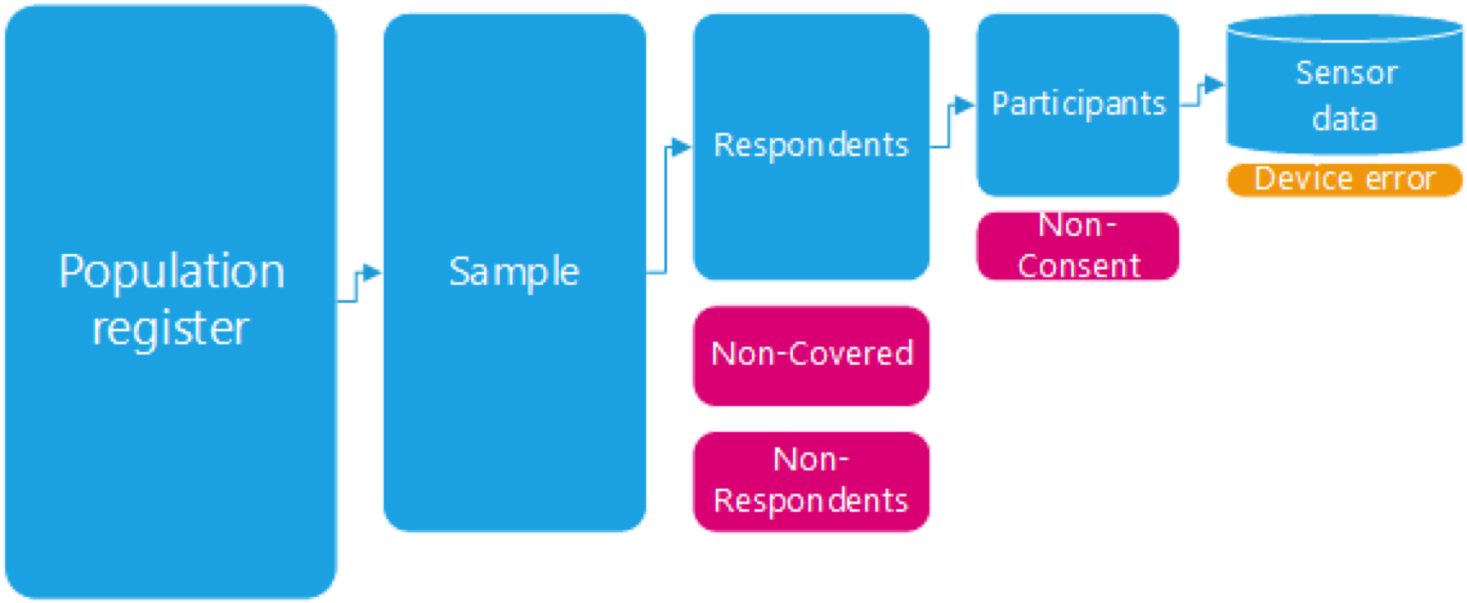
Source: Jäckle et al. (2018)

...a selection of research questions

- How do environmental factors affect happiness? (MacKerron & Mourato 2013)
- How do people interact in large social networks? (Stopczynski et al. 2014)
- How much do households spend on goods and services? (Jäckle et al. 2019; Wenz et al. 2018)
- What food and drinks do Americans acquire? (Yan et al. 2019)
- How do people find work after prison? (Sugie 2018)
- Does mental health of students change over the course of a term? (Wang et al. 2014)
- How do people move around in everyday life? (McCool et al. in preparation)
- What are the effects of unemployment? (Kreuter et al. 2018)
- How do people's home look like? (Ilic et al 2022)

Introducing “design” to Big Data

- Smartphone sensor data have many characteristics of Big Data
  - Large volume, high velocity, variety of data formats
- Combining passive smartphone data collection with self-reports through surveys introduces “design” to Big Data



How do people move around in everyday life?

(McCool, Lugtig, and Schouten, under review)

- Everyday mobility field test in the Dutch general population (Nov-Dec 2018)
  - Travel app of Statistics Netherlands (Android & iPhone)
  - Data collection for 7 days
  - N = 1,902
- Sensing location per second (when moving) & per minute (when still):
  - GPS
  - Wi-Fi
- Respondents eagerly provide additional information that helps understand travel behavior (label stops and motives for travel)

Recruitment (Lugtig et al. 2019)

- Invitation letter
- Website
- App Download
- Allow tracking

Centraal Bureau voor de Statistiek

<naam>
<adres>
<PC> <plaats>

ons kenmerk
onderwerp CBS-onderzoek
datum

CBS Heerlen
CBS-weg 11
6412 EX Heerlen

<Aanhef>

We zijn met z'n allen veel onderweg. Boodschappen doen met de fiets, wandelen met de hond, met de trein erop uit of met de auto naar het werk. Auto's, fietsen en voetgangers vechten om de beschikbare ruimte. Wat betekent dit voor ons? Kunnen we onze kinderen nog veilig naar school brengen op de fiets? Hebben we meer asfalt nodig? Of juist niet? Om dit soort vragen te beantwoorden voeren het CBS en het ministerie van Infrastructuur en Waterstaat het onderzoek 'Onderweg in Nederland' uit.

Voor dit onderzoek vraagt het CBS een klein aantal personen om met een app korte tijd bij te houden waar ze naar toe gaan. U bent daar één van. U vertegenwoordigt dus veel andere inwoners in Nederland. Voor gemeenten, provincies en voor het Rijk is dit onderzoek de belangrijkste bron van kennis over mobiliteit. Helpt u mee? Zo houden we Nederland samen bereikbaar. Nu en in de toekomst.

Als dank voor uw hulp krijgt u na afloop van het onderzoek **een cadeaubon van €20.**

Hoe kunt u meedoen?

1. Meedoen kan alleen met een smartphone.
2. Ga met uw smartphone naar de website van het onderzoek: www.tabiapp.eu of gebruik de QR code hiernaast.
3. Op de website kunt u de app downloaden.
4. Na het openen van de app vult u uw gebruikersnaam en wachtwoord in:

Gebruikersnaam: 4035
Wachtwoord: test

5. Het gebruik van de app is heel eenvoudig en wordt in de app zelf uitgelegd.

Arbeid en inkomen Economie Maatschappij Regio Corporate Cijfers ENGLISH

Onderzoeken Privacy Beloningen Contact

Deel deze pagina

CBS Verplaatsingen

Fijn dat u met ons op weg gaat!

Voor dit onderzoek is het nodig om een app te downloaden. De app houdt bij op welke plaatsen u bent en via welke weg u daar naartoe gaat. Wilt u een enkele keer uw locatie liever niet laten bijhouden, dan zet u de app gewoon even uit.

Wat vragen wij van u?

1) Installeer de app en laat deze **één week** aan staan.
2) Geef in de app aan waarom u ergens naar toeging en hoe u dat deed (bijvoorbeeld lopend, met de fiets of auto).

Het is heel eenvoudig om te doen en ook leuk om te zien. In de app leggen we uit hoe het werkt. Nieuwsgierig geworden? Download dan nu de app door op onderstaande knop te klikken. Klik daarna op 'installeren' als u daarom wordt gevraagd.

Installeren

Android

Open op je mobiel de Google Play Store en zoek naar **"CBS Verplaatsingen"**, of klik gewoon op de "Get it on Google Play" link beneden en klik op ***installeren***.

GET IT ON Google Play

iOS

Op je mobiel, open de App Store en zoek naar **"CBS Verplaatsingen"**, of klik gewoon op de "Available on the App Store" link beneden en klik op ***installeren***.

Available on the App Store

Uw gegevens zijn veilig

Direct naar
Hoe bedien ik de app in Android?
Hoe bedien ik de app in iOS?
Veelgestelde vragen

Recruitment (Lugtig et al. 2019)

- Invitation letter
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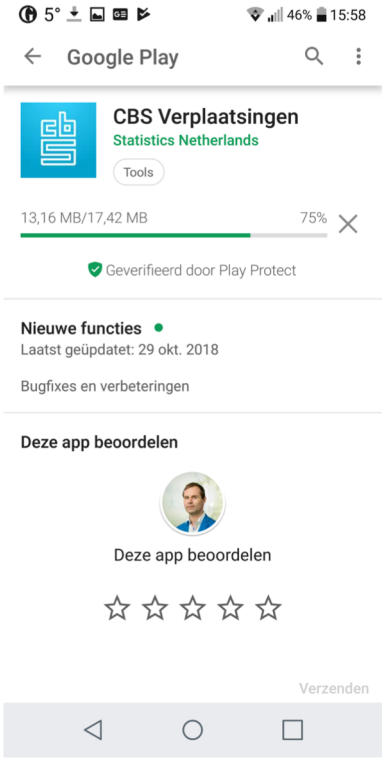
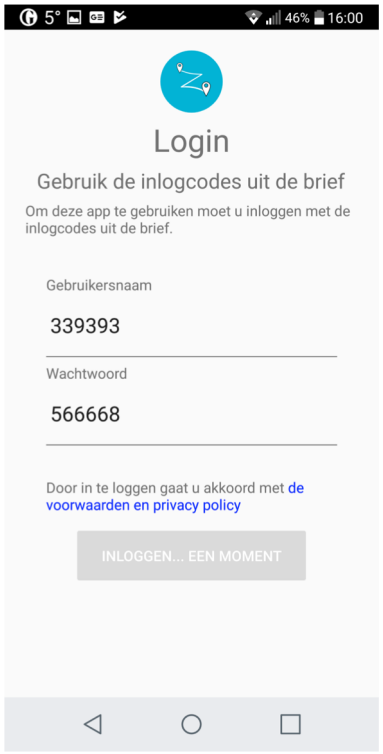
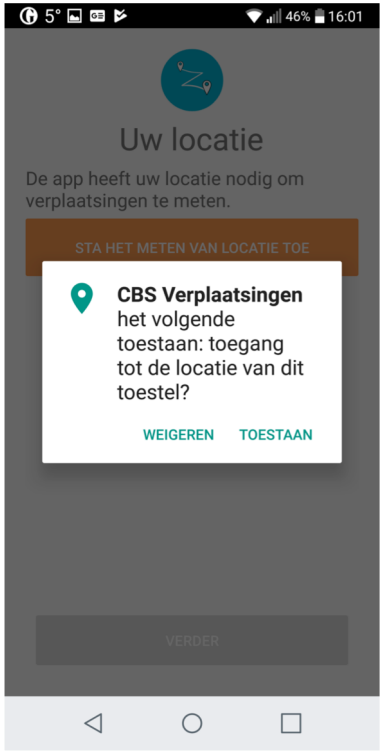


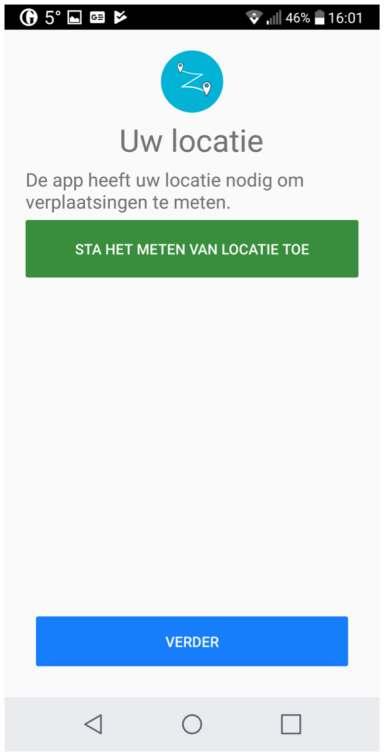
Google play store



Log in with credentials

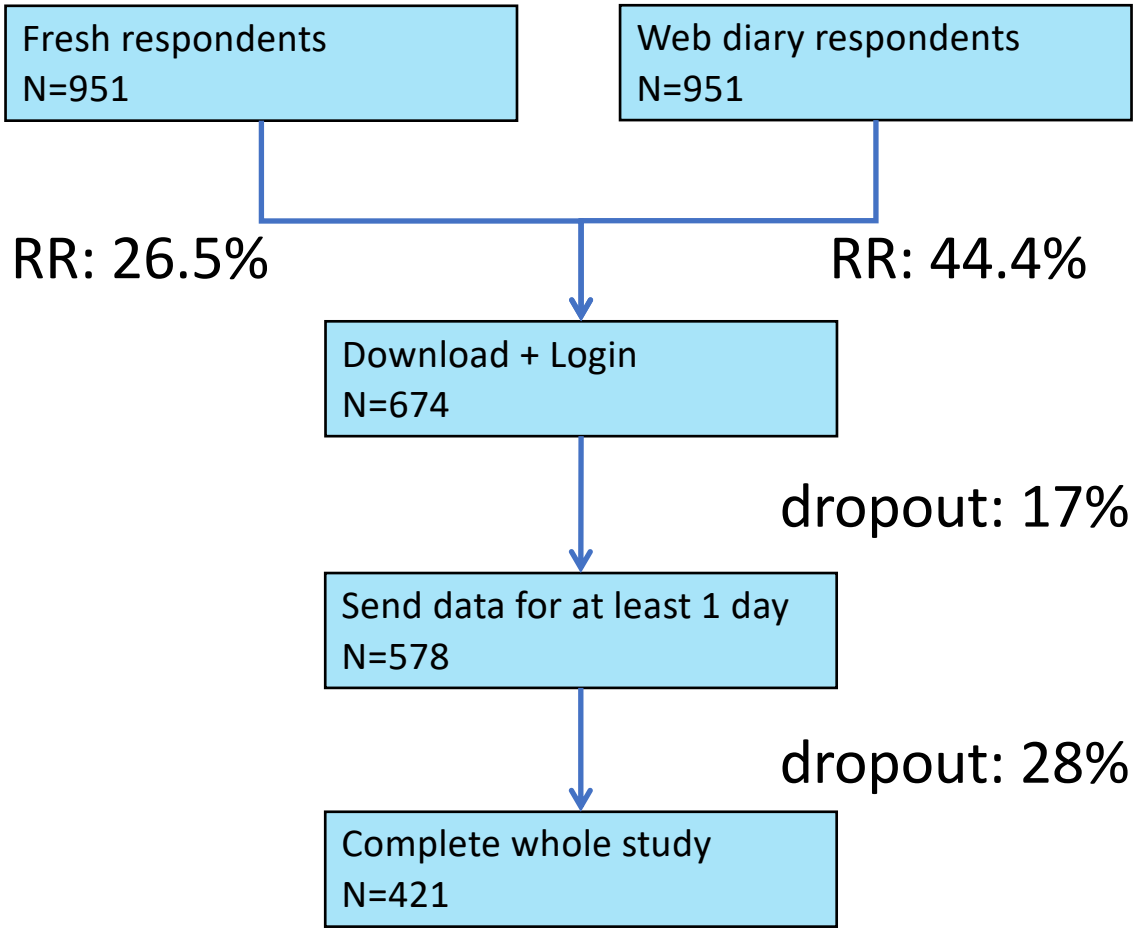


Allow GPS tracking



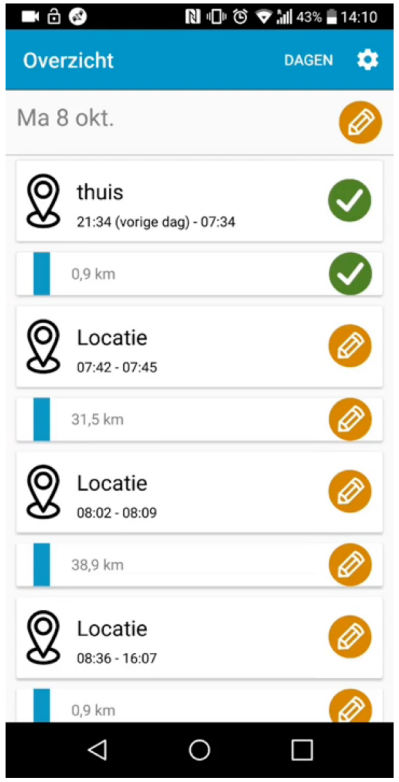
Ready to use

Recruitment (Lugtig et al. 2019)

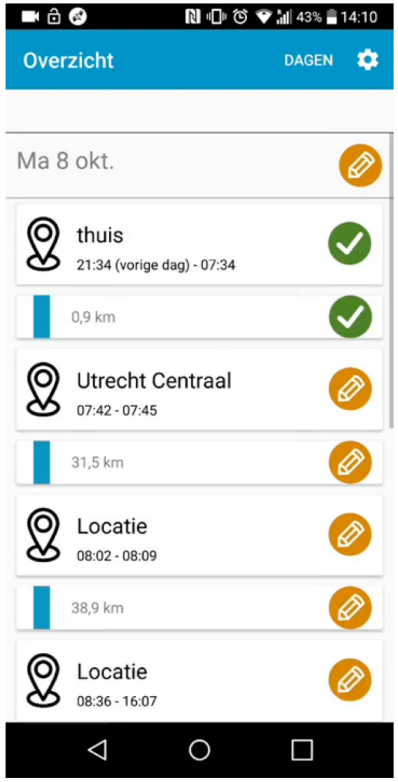


How do people move around in everyday life?

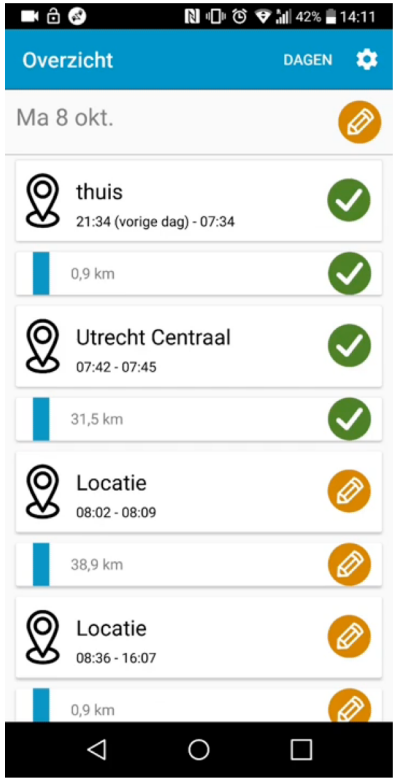
(McCool, Lugtig, and Schouten, 2021)



Daily overview



Questions about stops



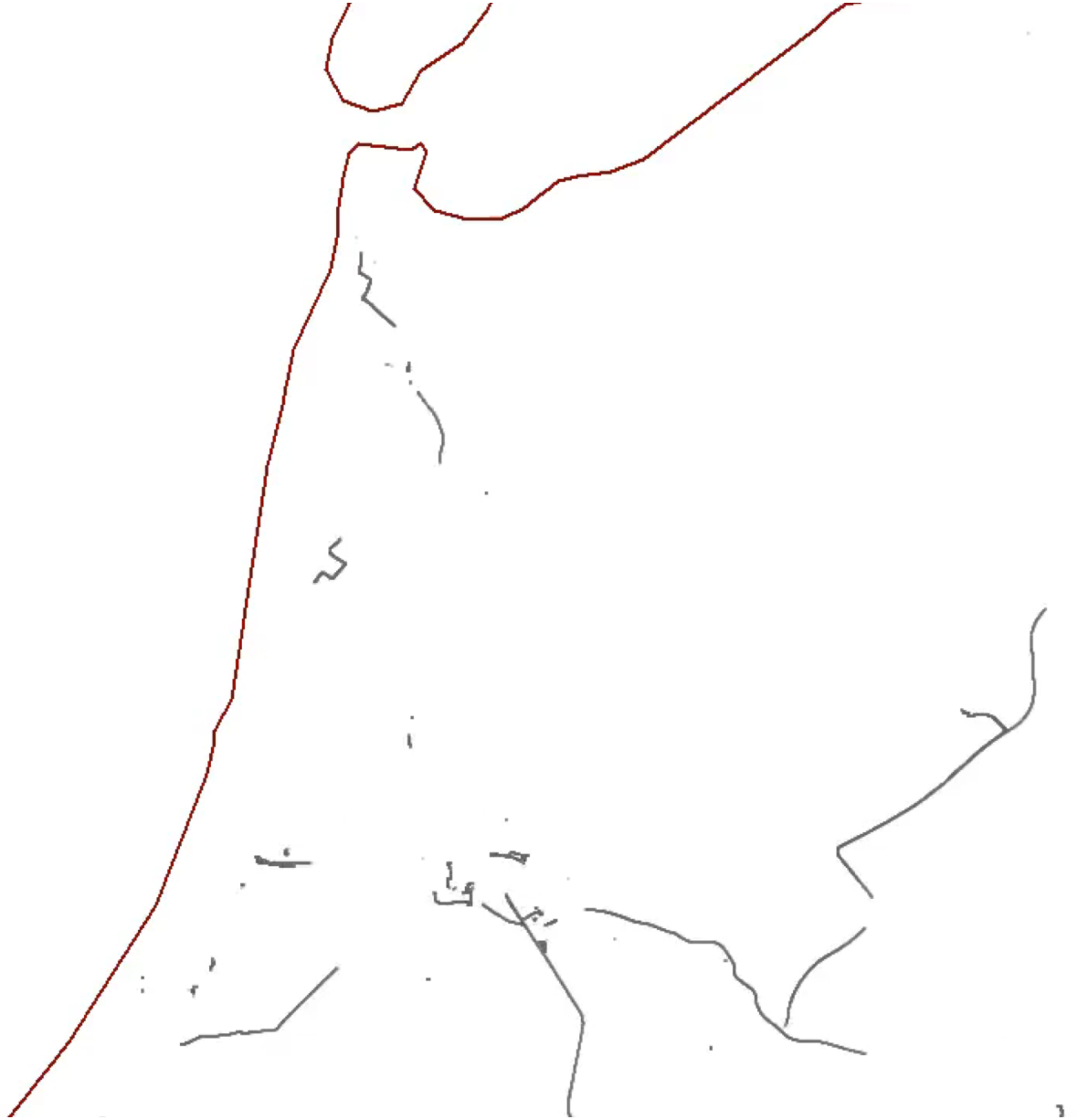
Questions about trips

How do people move around in everyday life?

(McCool, Lugtig, and Schouten, 2021)

- One week travel

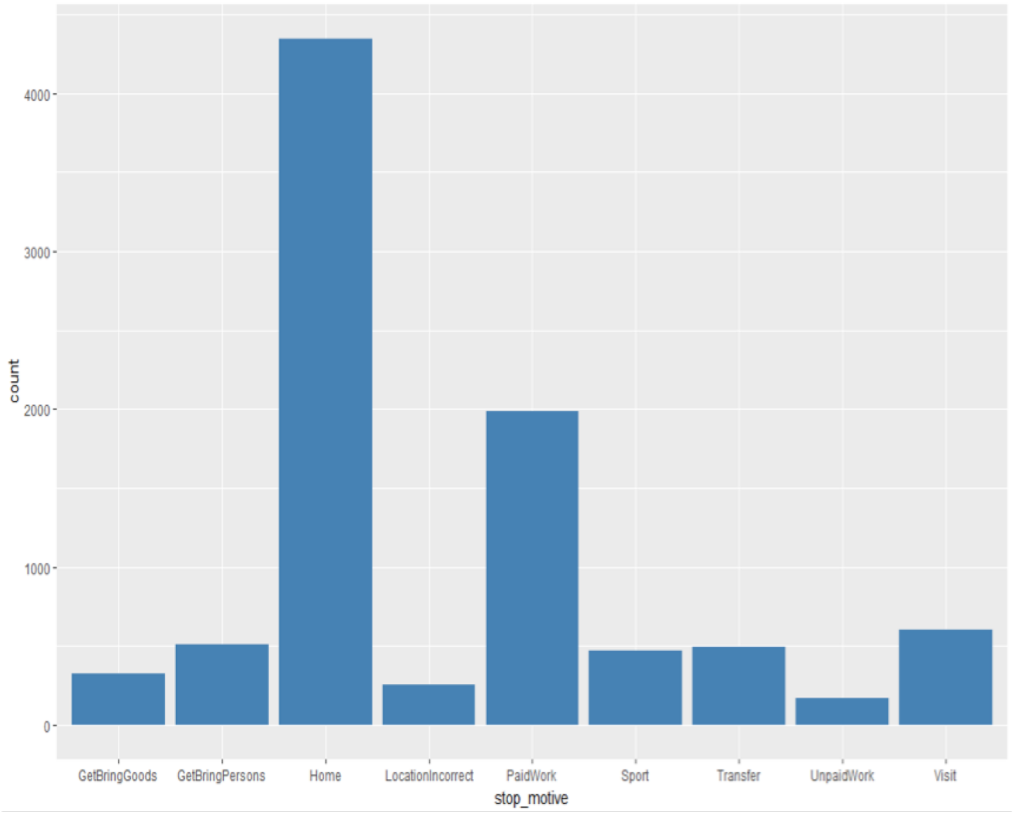
07:30



How do people move around in everyday life?

(McCool, Lugtig, and Schouten, 2021)

- 22,000 stops
  - 13,000 (60%) labeled
  - Overall 50% of respondents give complete/almost complete details



Raw data

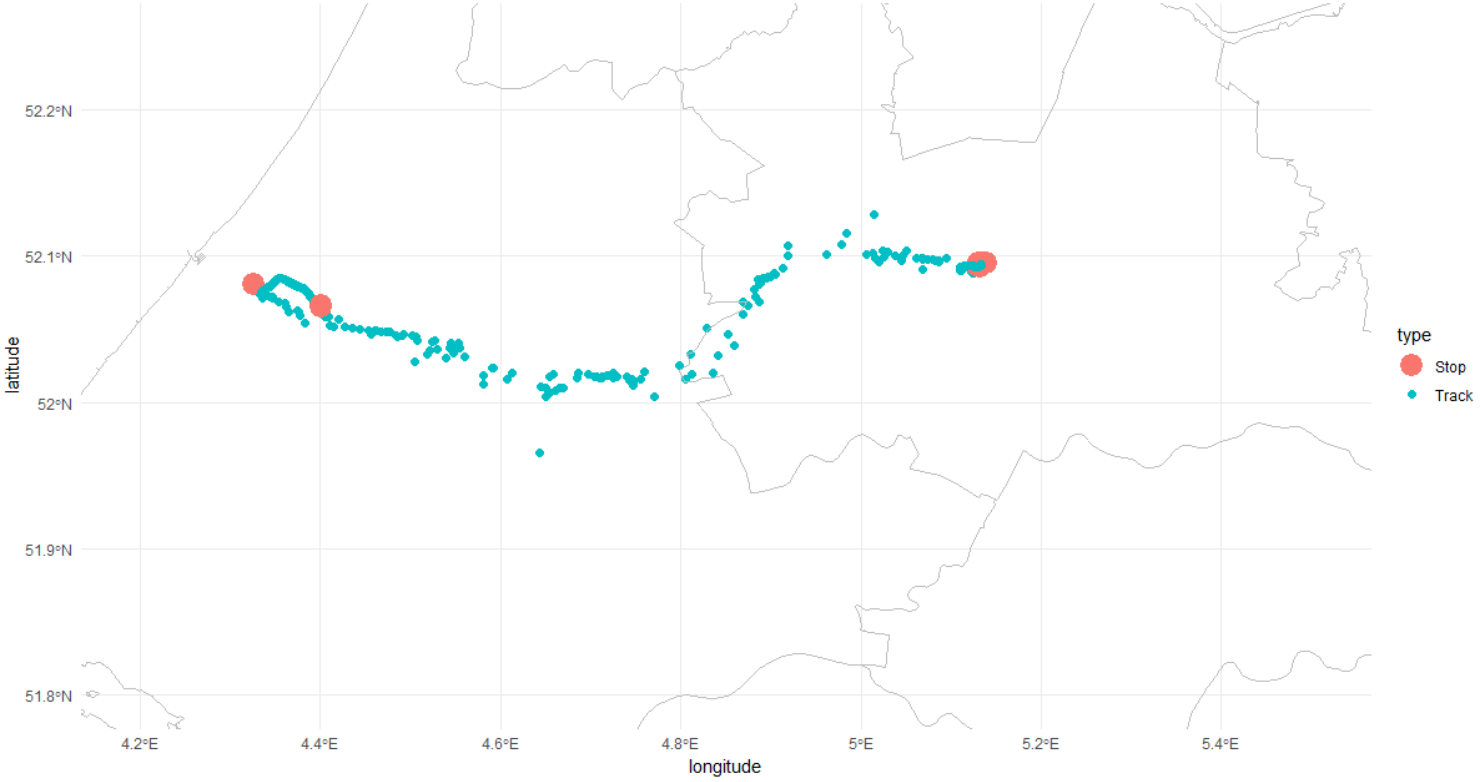
	device_id	latitude	longitude	accuracy	speed	altitude	timestamp
1:	23	52.09460	5.134593	15.204	0	54.7	2018-10-31 22:53:22
2:	23	52.09460	5.134593	15.204	0	54.7	2018-10-31 22:54:22
3:	23	52.09460	5.134593	15.204	0	54.7	2018-10-31 22:56:40
4:	23	52.09460	5.134593	15.204	0	54.7	2018-10-31 22:57:40
5:	23	52.09460	5.134593	15.204	0	54.7	2018-10-31 22:59:05

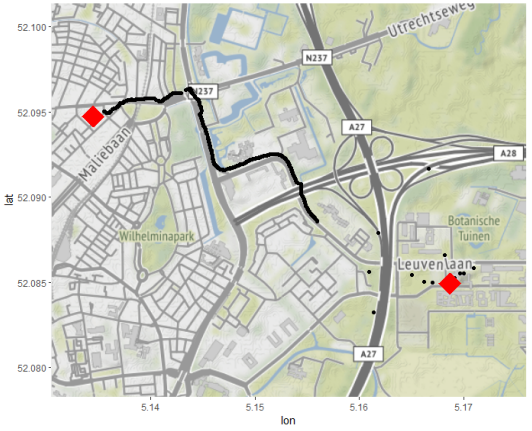
38524:	23	52.09464	5.134572	15.175	0	54.7	2018-11-12 00:00:33
38525:	23	52.09464	5.134572	15.175	0	54.7	2018-11-12 00:00:33

	device_id	local_stop_id	begin_timestamp	end_timestamp
1:	23	7	2018-10-31 17:05:47	2018-10-31 17:11:51
2:	23	11	2018-10-31 17:26:56	2018-10-31 17:31:39
3:	23	5	2018-10-31 17:32:51	2018-10-31 17:40:09
4:	23	4	2018-10-31 17:45:13	2018-10-31 19:03:58
5:	23	8	2018-10-31 19:04:08	2018-11-01 12:53:08
6:	23	9	2018-11-01 13:00:52	2018-11-01 15:47:21

	device_id	local_stop_visit_id	motive
1:	23	3	Home
2:	23	2	PaidWork
3:	23	1	Home
4:	23	7	Transfer
5:	23	6	Transfer
6:	23	4	Home

Making inference from raw data

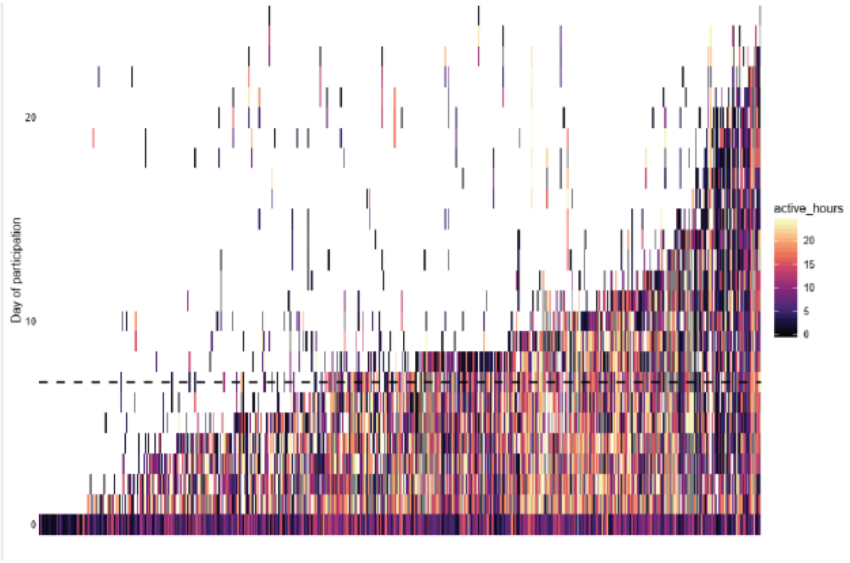




Source: McCool et al. (2019)

Errors during data collection & Missing data

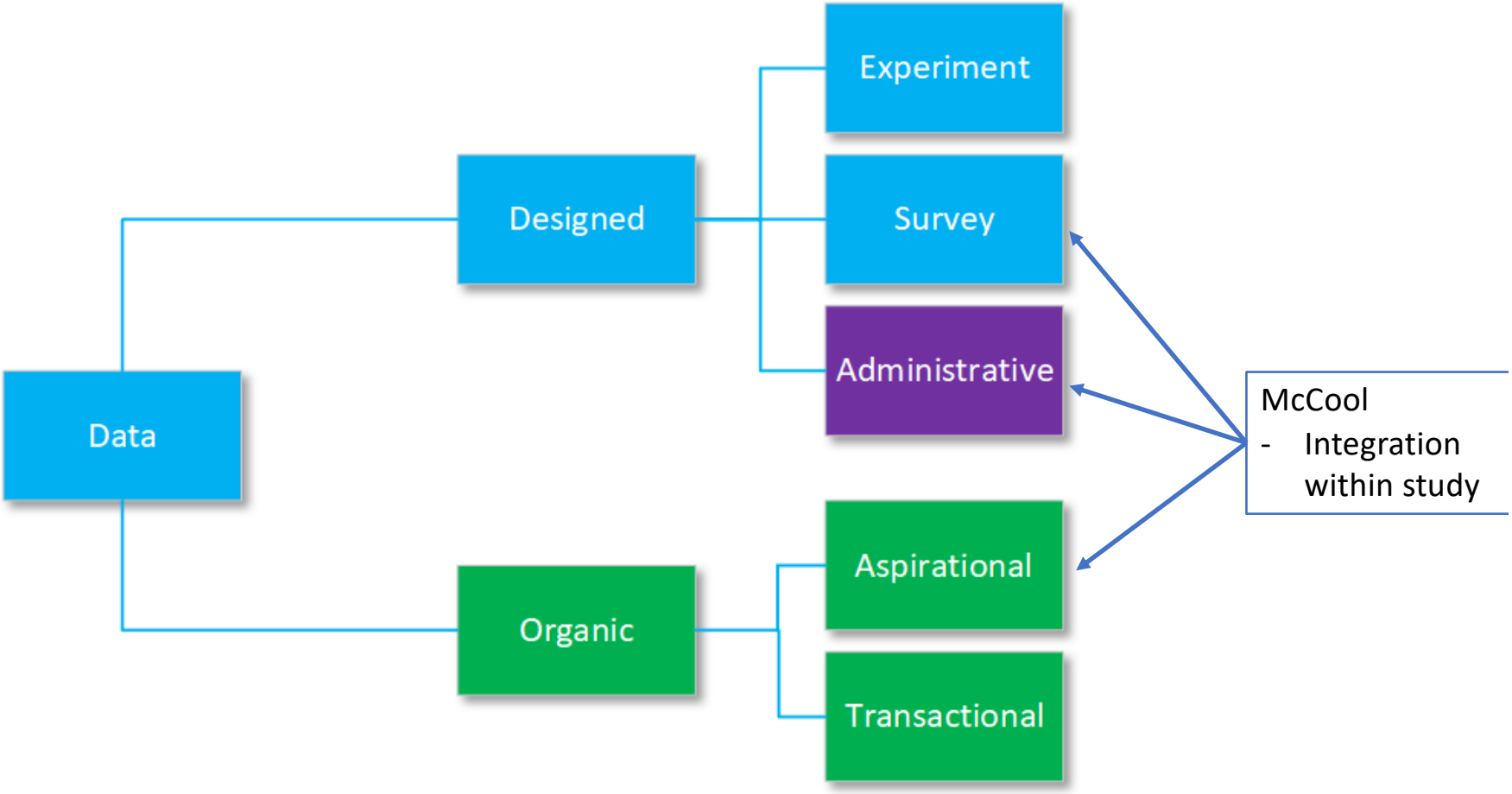
- Sensor-based errors
- Missing data
  - Technical issues: e.g.,
    - Phone out of power or sleep mode
    - iOS blocks collection of location in background
  - Noncompliance: e.g.,
    - Missing permissions
    - Mobile data disabled
    - Leaving phone at home
    - Turning app off at certain locations
- Erroneous data
- Providing feedback & measurement reactivity



Active hours per user (McCool et al. 2019)

Storage & Costs

- One person's GPS coordinates collected every second/min for 7 days would result in on average 60.000 data points per person
- Think whether you really need this amount of data!
- Most systems store data first on device and transmit them to server once connected to Wi-Fi
- Processing data on device and only transmitting aggregated data saves storage space
- Besides storage, costs can include:
  - App/In-browser measurement development
  - Incentives
  - Data handling
  - Helpdesk

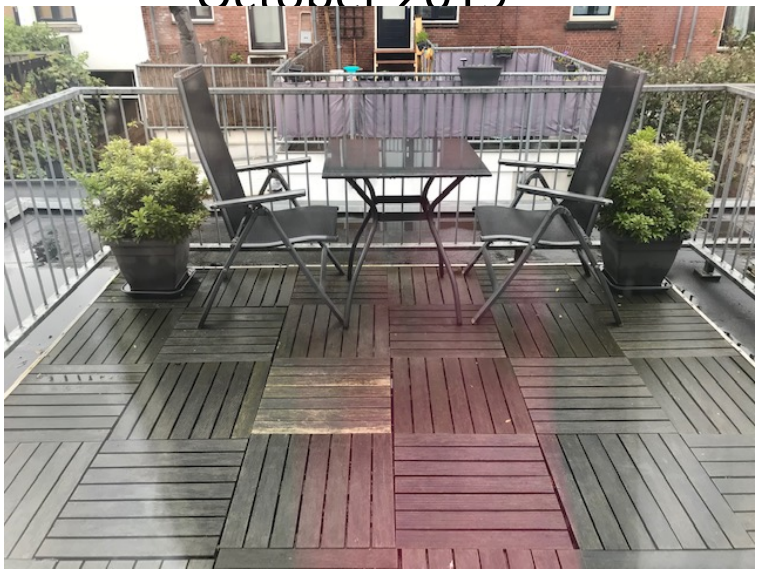


(Source: Kreuter 2018)

Picture project (Ilic et al 2022)

Note: pictures recreated, not actual pictures submitted by respondents

- 2700 LISS respondents on their mobile phone
  - 1759 respondents
- Asking for sensor measurements in context
  - Photo of favorite place
  - Photo of garden
  - Photo of heating elements
- October 2019



Experiment with information

- 1. Pictures:
  - Would you be willing to take a picture of your favorite place/garden/heating system? Yes/no
  - Are you willing to share this picture?
- 2. Text:
  - Can you describe your favorite place/garden/heating system?
- 3. choice:
  - Would you rather take a picture or provide text answers in this study?

Questions

1. Willingness? What happens in choice-condition?
2. Quality of measurements
   - focus here on heating system
3. What provides better data? Text, pictures, or choice?

Analyses are results from thesis work of Goran Ilic

Choice does not lead to lower willingness

- Of those who had a choice, about 57% opted for photos
  - And then ~80% took a picture

Experimental Condition	**Fav. place**	**Outdoors**	**Heating**
Picture condition: Took a photo	43% (540)	29% (521)	36% (444)
Text condition: Answered the question	98% (655)	99% (632)	67% (549)
Choice: picture & took photo	48% (564)	31% (537)	37% (479)

Note: eligible n in parentheses

Quality of picture data (heating)

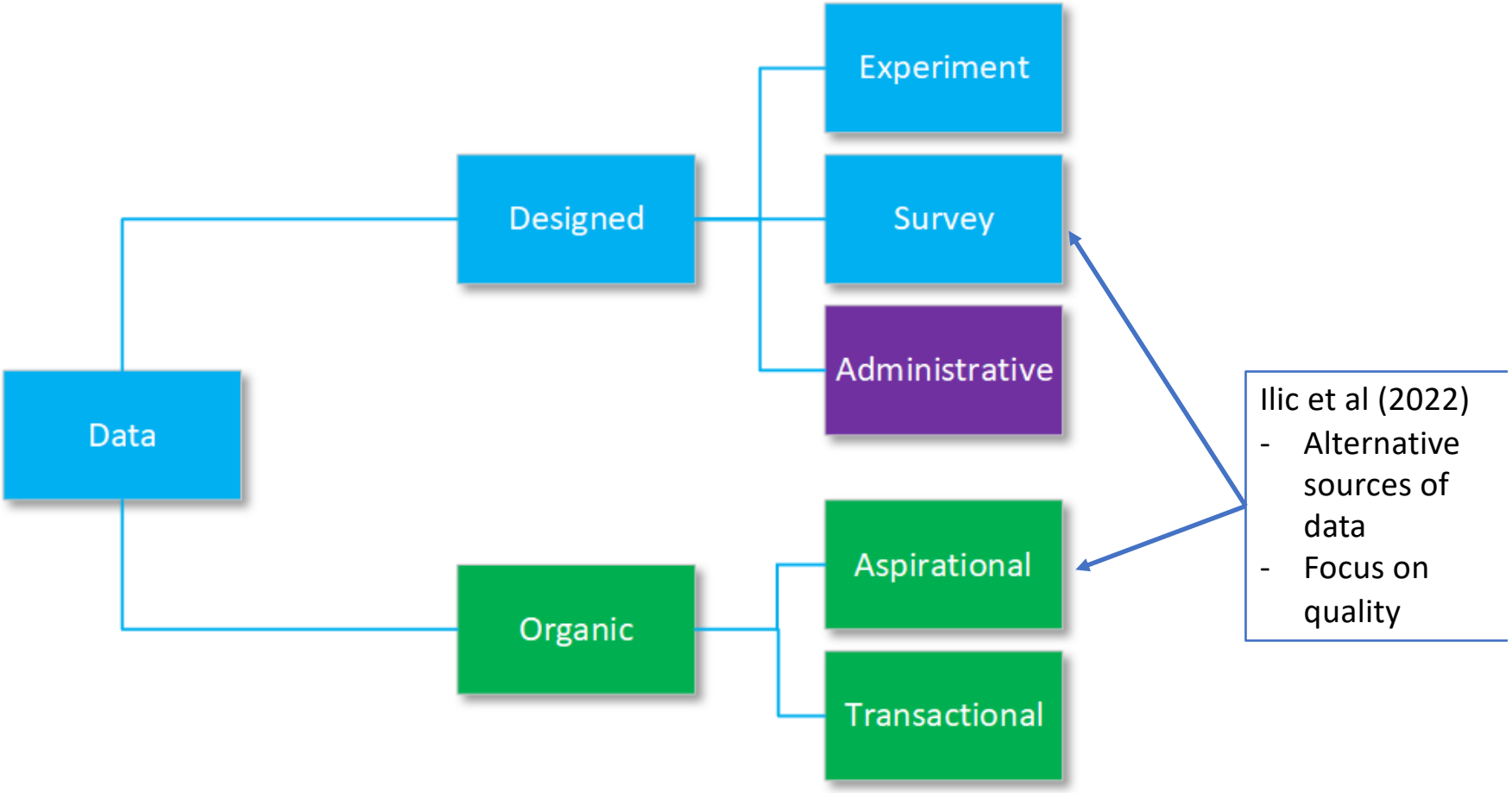
	Sample size
Eligible for picture	720
Submitted a picture	321 (45%)
No Privacy issues with pics	309
In line with task	281 (88%)
Info at picture:	
• "good" quality (using OCR)	• 212
• Partly usable	• 67
• unusable	• 2
Extract good info (brand+type)	142 (44% of pictures, 20% overall)

Quality of text data (heating)

	Sample size
Eligible for text	953
Provided text	489
- Uninformative	104
- Brand + type	142 (29% of texts, 15% overall)

Conclusions (pictures)

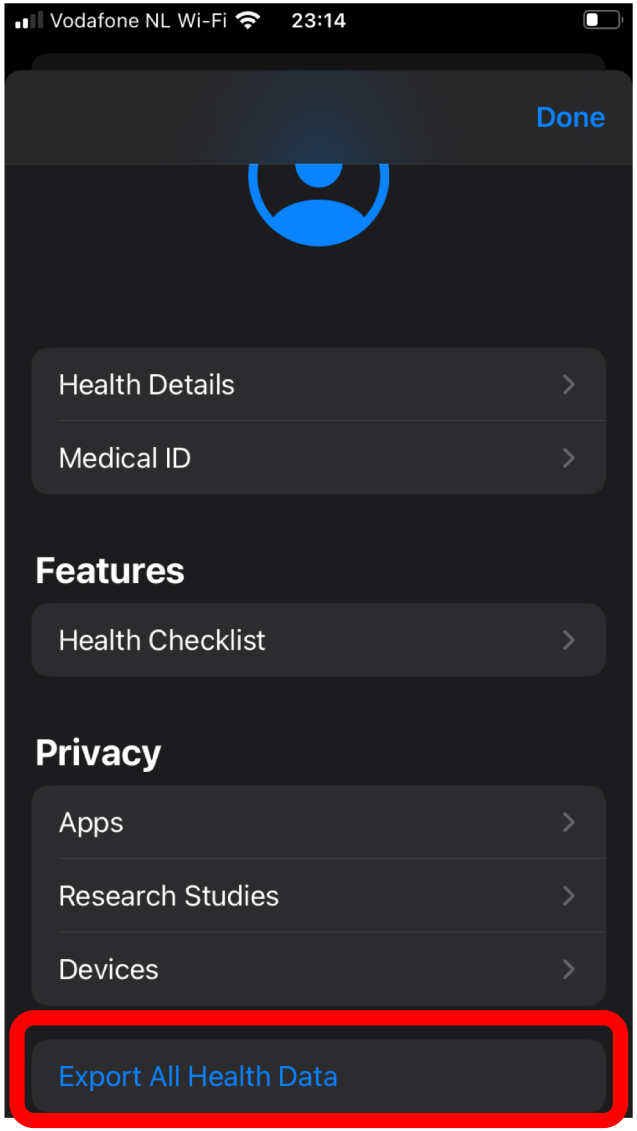
- Choice does not affect willingness for pictures
  - If anything, increases willingness
- People more willing to provide text answers
  - But answers of lower quality than pictures
- To do:
  - Selection bias?
  - Measurement now quantified as good/bad



(Source: Kreuter 2018)

Take home exercise

- If you have an iPhone or an Apple watch (or your friend with an iPhone graciously shares data with you or you google how to replicate it for android)
- Download your apple health data, prepare it for analysis and find out something about yourself (see next slide)



Take home exercise

- Go to “Health” -> click on profile -> Download All Health Data
- Follow the steps from here to prepare for analysis: https://taraskaduk.com/posts/2019-03-23-apple-health/
- You will need these packages and use only if you want to change time zones, otherwise comment out #endDate = ymd_hms(endDate,tz="America/New_York"),

```
library(XML)
library(tidyverse)
library(lubridate)
library(scales)
library(ggthemes)
library(dplyr)
library(magrittr)
library(stringr)
library(ggplot2)
```

- Find out about something about yourself! e.g., your average step count, how many steps you go by day of the week and when, or something more interesting
- Send me your code and your result (e.g., a plot) and I will tell Peter ☺

Take home exercise

- It is optional! So no stress…

***German “entspannen” = relax**

Questions? Comments?

Now or contact me at b.struminskaya@uu.nl

References & Additional reading

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