EMOS webinar
"smart surveys"

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Agenda: smart surveys what, why and how

- What is a smart survey?
- Why?
- Does it work?
  - Do we get better data?
  - Business cases
- How to actually do it?

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What is a smart survey?

1. A survey
2. A ‘smart’ element
   - Sensors to collect other data: pictures, audio, locations, movements, etc.
3. Integrate the survey and smart element
   - After data collection: e.g. Fitbits with questionnaires on activities
   - During data collection: smartphone apps
     - Sensors help to make task easier
     - Sensor data are often processed on phone
     - Respondents can interact with sensor data

Schouten & Lugtig (in review). Combining surveys and organic data from sensors in Designed Big Data. Three case studies. *Journal of Official Statistics*

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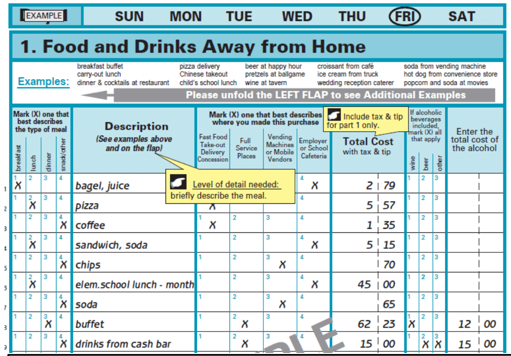
Why smart surveys?

- **Push** away from surveys
  - 1. surveys are costly and time-consuming
  - 2. topic: low centrality
  - 3. topic: high burden
- **Pull** towards smart surveys
  - 1. high availability of organic data
  - 2. costs of collecting and processing low
  - 3. high quality of data

Schouten & Lugtig (in review). Combining surveys and organic data from sensors in Designed Big Data. Three case studies. *Journal of Offficial Statistics*

Potential topics

- **Push** away from surveys
  - 1. surveys are costly and time-consuming
  - 2. topic: low centrality
  - 3. topic: high burden
- **Pull** towards smart surveys
  - 1. high availability of organic (smart) data
  - 2. costs of collecting and processing low
  - 3. high quality of data



EXAMPLE — SUN MON TUE WED THU FRI SAT

1. Food and Drinks Away from Home

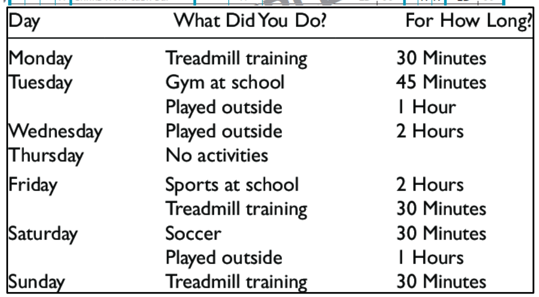
Examples: breakfast buffet, carry-out lunch, dinner & cocktails at restaurant, pizza delivery, Chinese takeout, child's school lunch, beer at happy hour, pretzels at ballgame, wine at tavern, croissant from café, ice cream from truck, wedding reception caterer, soda from vending machine, hot dog from convenience store, popcorn and soda at movies

Please unfold the LEFT FLAP to see Additional Examples

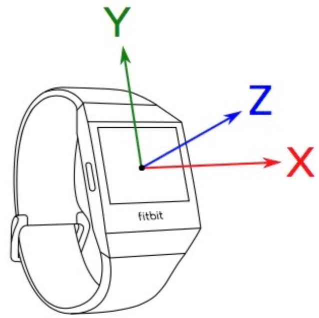
Level of detail needed: briefly describe the meal.

Include tax & tip for part 1 only.

	breakfast	lunch	dinner	snack/other	Description (See examples above and on the flap)	Fast Food Take-out Delivery Concession	Full Service Places	Vending Machines or Mobile Vendors	Employer or School Cafeteria	Total Cost with tax & tip	wine	beer	other	Enter the total cost of the alcohol
1	X				bagel, juice				X	2.79				
2		X			pizza	X				5.57				
3				X	coffee	X				1.35				
4		X			sandwich, soda				X	5.15				
5				X	chips			X		.70				
6		X			elem.school lunch - month				X	45.00				
7				X	soda			X		.65				
8			X		buffet		X			62.23	X			12.00
9				X	drinks from cash bar		X			15.00		X	X	15.00



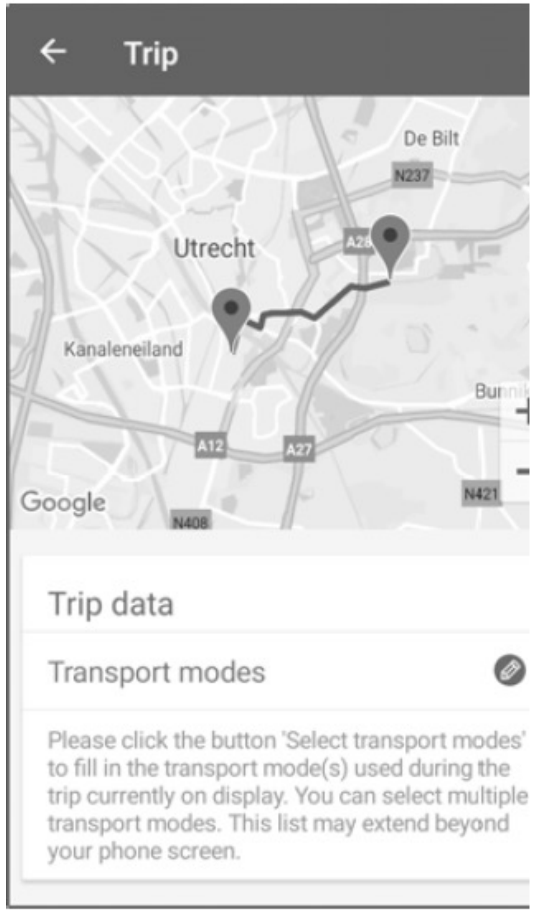
Day	What Did You Do?	For How Long?
Monday	Treadmill training	30 Minutes
Tuesday	Gym at school	45 Minutes
	Played outside	1 Hour
Wednesday	Played outside	2 Hours
Thursday	No activities	
Friday	Sports at school	2 Hours
	Treadmill training	30 Minutes
Saturday	Soccer	30 Minutes
	Played outside	1 Hours
Sunday	Treadmill training	30 Minutes



Schouten & Lugtig (in review). Combining surveys and organic data from sensors in Designed Big Data. Three case studies. *Journal of Offficial Statistics*

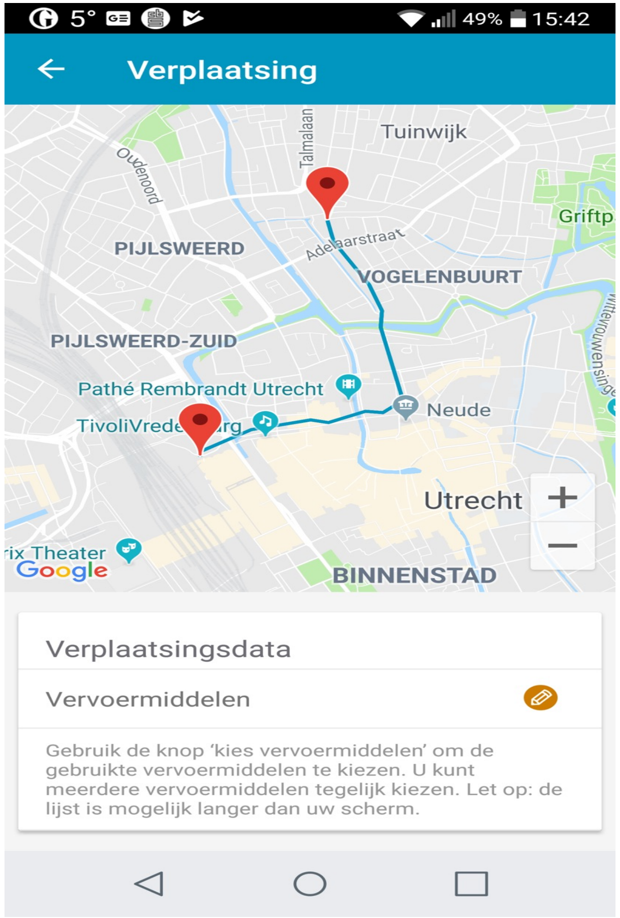
An example: smartphone travel study

- OLD: OdIN (On-route In the Netherlands)
  - Old: paper, revently: web-diary study
  - 2 days of travel data
  - start, endtime, location, travel modes, etc.
- New: TABI smartphone travel app
  - 1 week continuous tracking
  - Wifi/GPS
    - Every minute when stationary
    - Every second when moving

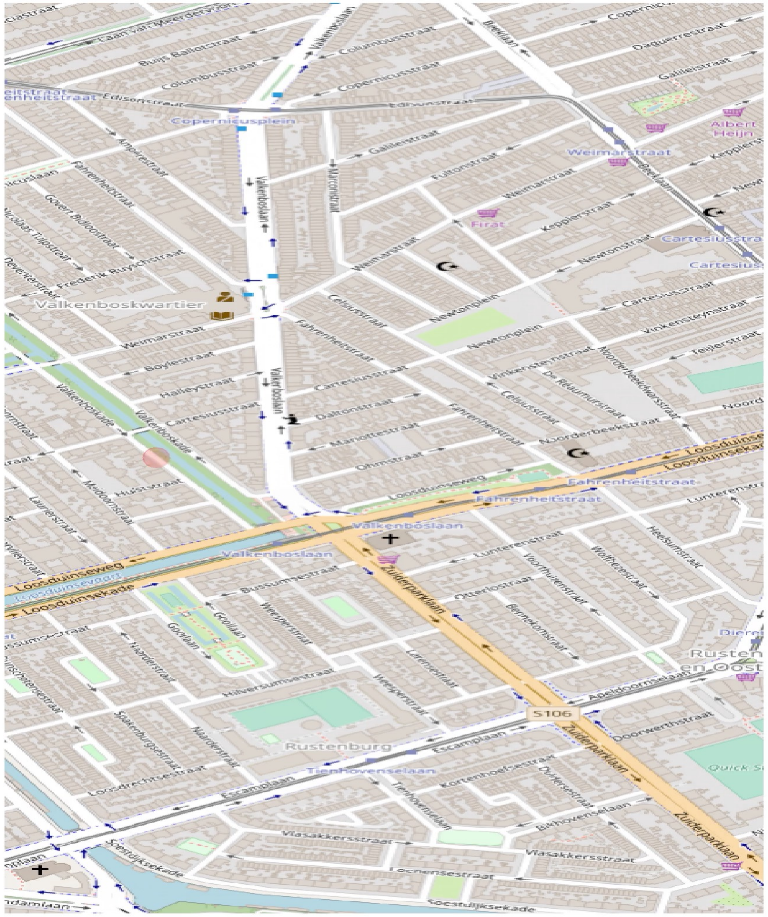


The Tabi app (2018)

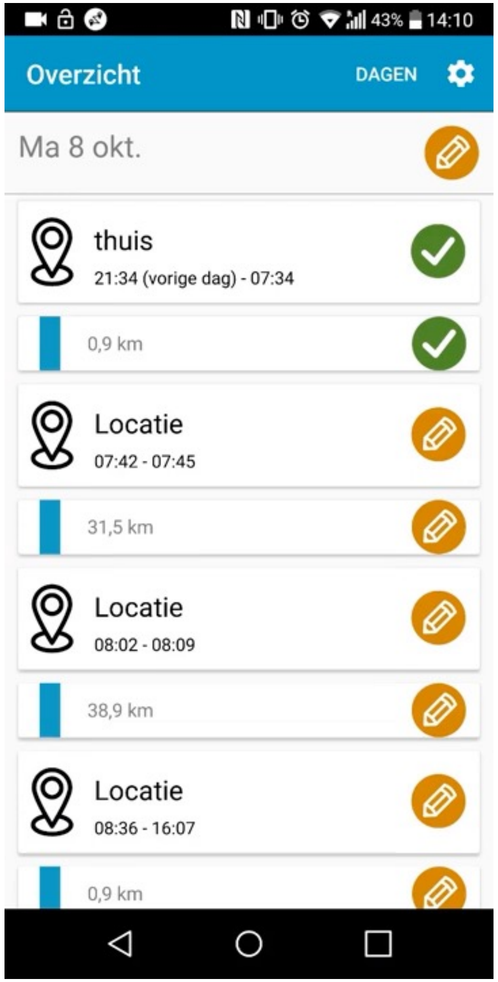
- Develop everything ourselves
  - Transparency, control
  - Open-source: https://gitlab.com/tabi/tabi-app
  - Modular design: parts can be recycled
- App should work on all smartphones
  - In practice: < 4 years old
  - In practice difficult: updates, brand varieties
  - App should not drain battery
- Low respondent burden
  - Few (or no) questions

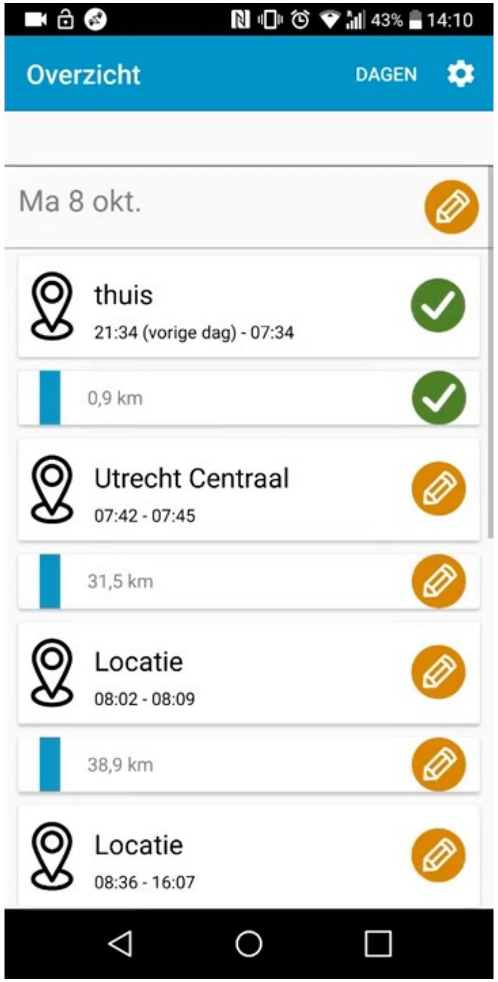


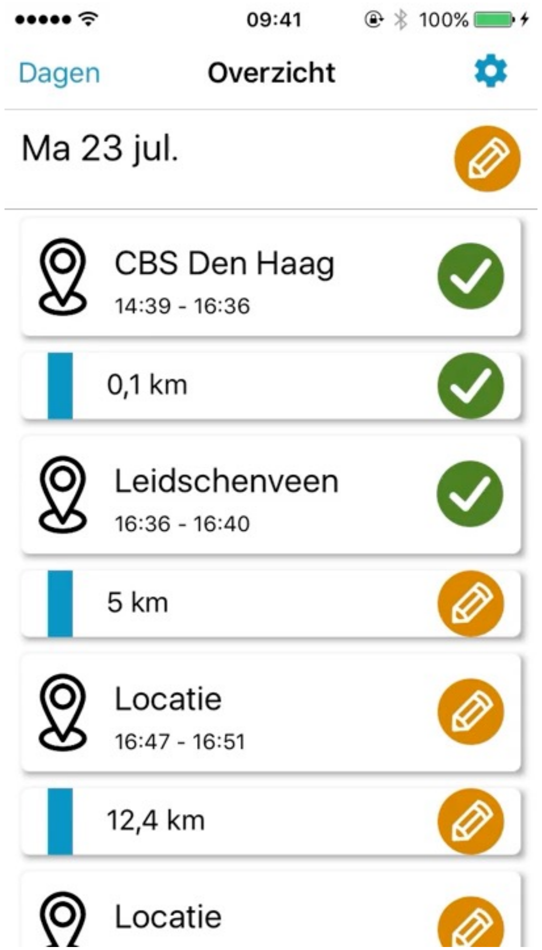
The app: Location measurements



The app: Diary and annotations







1 week travel in Dutch population - TABI app

Skip to trips

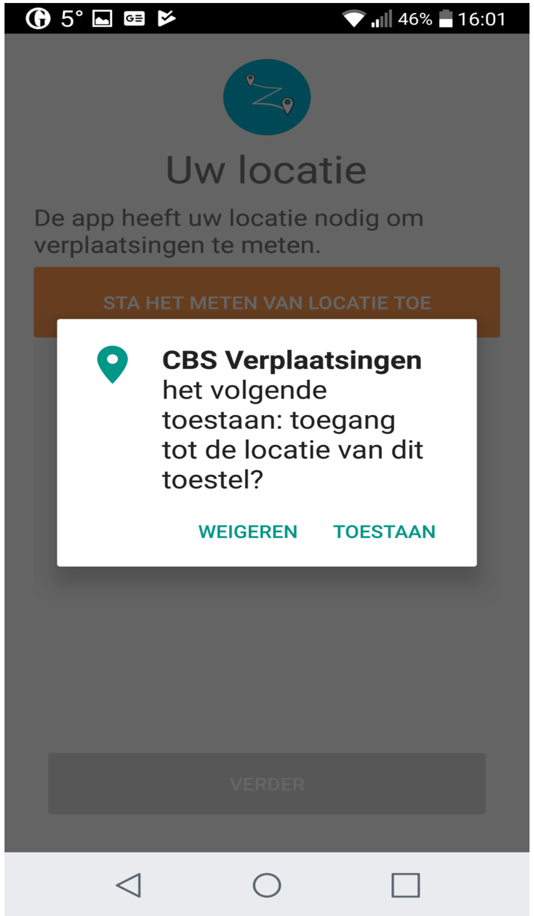
Does it work? Experiments...

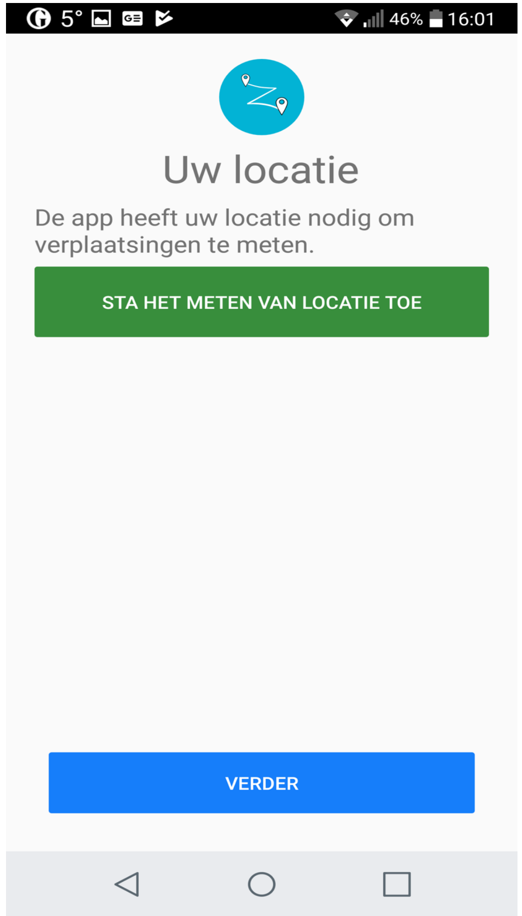
- Experiment 1: Recruitment (n=1902)
  - Fresh cross-section taken from population register (n=951)
  - ODiN Web diary respondents in September 2018 (n=951)
- Experiment 2: Incentives
  - Incentive 5 + 5 + 5 (before, registering, after 7 days)
  - Incentive 5 + 10 (before, after 7 days)
  - Incentive 5 + 20 (before, after 7 days)
- Experiment 3: how to detect a stop? (not today)

- In 2023 experiments with mixed-mode collection -> app-web (not today)

Fieldwork

- 1. invitation letter
  - 1b. website
- 2. download app
- 3. login
- 4. allow location measurements





Results recruitment

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Fresh respondents
N=951

Earlier Web diary respondents
to ODIN study
N=951

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Results recruitment (1)

Fresh respondents
N=951

Web diary respondents
N=951

RR: 26,5%

RR: 44,4%

Download + Login
N=674

Results recruitment (2)

Fresh respondents
N=951

Web diary respondents
N=951

RR: 26,5%

RR: 44,4%

Download + Login
N=674

dropout: 17%

Send data for at least 1 day
N=578

Results recruitment (3)

Fresh respondents
N=951

Web diary respondents
N=951

RR: 26,5%

RR: 44,4%

Download + Login
N=674

dropout: 17%

Send data for at least 1 day
N=578

dropout: 28%

Complete whole study
N=421

Complete Responses: 22,1% of sample

Stage 1: Registration (yes=674) Average Marginal effects	
Sample: ref= fresh	.16*
Incentive (ref=5+5+5)	
5 + 10	.07*
5 + 20	.10*
Age (ref =18-25)	
26-45	-.14*
46-65	-.20*
>65	-.28*
Drivers license (ref=no)	.05
Car owner (ref=no)	.02
Moped owner (ref=no)	.02
Highest level of education (ref = primary school)	
Lower secondary	-.01
Upper secondary/vocational	.09
Bachelor	.20*
Master	.19*
Unknown	.05
Marital status (ref=married)	-.06*
Origin (ref = Dutch)	
Non-westerm	-.11
Western	-.05
Income (ref = Q1-20)	
21-40	-.10*
41-60	.03
61-80	.08
81-100	.07
unknown	.02
[illegible]	[illegible]

Effects on NR (conditional)

Incentives:

- 10 euro 7% higher than 5+5
- 20 euro another 3% higher

Covariates

- 20-28% lower for >65 age
- 20% higher for higher educated

Stage 1: Registration (yes=674) Average Marginal effects	
Sample: ref= fresh	.16*
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21-40	-.10*
41-60	.03
61-80	.08
81-100	.07
unknown	.02
Female (ref = male)	[illegible]

NO interaction effects!

Nonresponse bias does not differ by:

- Incentive groups
- Sample groups

Lugtig, Roth & Schouten (2022) Nonresponse analysis in a longitudinal smartphone-based travel study. *Survey research Methods*

	Number of tracks	Number of unique locations per track	Average distance per trip (in meters)	Average speed per track (in m/s)	Average 95 percentile speed per track (in m/s)
Car	2738	444	5556	10.6	20.2
On foot	1873	30	150	1.4	3.4
Bike	995	260	1473	4.3	6.6
Train	197	526	23521	24.2	40.6
Electric bike	193	228	1729	5.0	8.1
Multiple transport modes	173	453	5607	4.4	16.6
Other	60	206	1322	3.4	6.8
Bus	59	668	5540	6.3	16.6
Wrong measurement	54	9	93	0.6	7.2
Truck	49	890	11236	11.6	21.3
Tram	35	419	3775	4.8	14.5
Scooter	34	375	2712	7.4	9.3
Metro	21	238	5400	9.4	26.0
Motor	7	18	23650	14.3	NA

Table 5.1: Modes of transport reported by respondents, along with characteristics of the trip

Some differences labeled/unlabeled trips

	Labelled trips	Unlabelled trips
median data points	347	238
median duration	553 sec	498 sec
median distance	2277 m	1707 m
% trips $\leq$ 500m	20.5%	27.4%
% E-bike trips	3.44%	7.72%*
% bike trips	17.84%	10.02%*
% car trips	50.98%	35.03%*
% metro trips	.35%	2.19 %*
% bus trips	1.04%	7.74%*
% scooter trips	.67%	1.66%*
% train trips	4.13%	5.98%*
% tram trips	.44%	2.23%*
% User errors	.65%	2.07%*
% walk trips	21.10%	27.46%*

Smeets, Lugtig & Schouten (in review) Automatic travel mode prediction in a national travel study. JRSS:A

App = better at short trips

	Labelled trips	Unlabelled trips	ODiN 2018 total
median data points	347	238	NA
median duration	553 sec	498 sec	900 sec
median distance	2277 m	1707 m	3000 m
% trips $\leq$ 500m	20.5%	27.4%	13.1%
% E-bike trips	3.44%	7.72%*	3.77%
% bike trips	17.84%	10.02%*	26.41%
% car trips	50.98%	35.03%*	43.00%
% metro trips	.35%	2.19 %*	.81%
% bus trips	1.04%	7.74%*	2.33%
% scooter trips	.67%	1.66%*	.72%
% train trips	4.13%	5.98%*	2.83%
% tram trips	.44%	2.23%*	.80%
% User errors	.65%	2.07%*	NA
% walk trips	21.10%	27.46%*	19.30%

App: more walks, fewer bike trips

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median data points	347	238	NA
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% car trips	50.98%	35.03%*	43.00%
% metro trips	.35%	2.19 %*	.81%
% bus trips	1.04%	7.74%*	2.33%
% scooter trips	.67%	1.66%*	.72%
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% tram trips	.44%	2.23%*	.80%
% User errors	.65%	2.07%*	NA
% walk trips	21.10%	27.46%*	19.30%

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Does it work?

- Respondents can be freshly recruited into smart surveys
  - A lot of work in panel context however, which brings benefits
- Measurement overall better with app
  - But some technical issues
  - And a lot of modeling effort
  - New statistics wanted?
- Large Nonresponse bias
  - Age and level of education
  - Incentives work

- Business case:
  - length of fieldwork period
  - Infrastructure costs

YES

3 minute pause for questions

How to do a smart survey?

- Trusted Smart Statistics (2020-2022)
- Smart Survey Implementation (2023-2025
  - Microservices for handling sensors
  - Methodology
    1. Recruitment
    2. Machine Learning
    3. User Interaction
    4. Mode effects
  - Legal ethical, data lifecycle, governance

Household budget Survey and microservices

Youtube video:
Hbits (2023)
https://www.youtube.com/watch?v=BvmD5Zqv27s

Methodology: recruitment

- What do we know about what smart surveys:

- Survey design features
  - Sponsor, incentives, length of data collection, interviewers, control over data collection process, transparancy, app
- Respondent characteristics
  - Smartphone usage, privacy concerns, socio-demographic (education, age)

See Bucher, Keusch, de Viitis, Fausti, Inglese, van Tienoven, McCool, Struminskaya & Lugtig (2023) Smart Survey deliverable M6: review stage.

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1. Methodology: recruitment

- What will we know next year
- Experiments in Norway, Italy, NL, Germany, Belgium
  - How to download app
  - Incentives
  - Reminders
  - Using web and mail as secondary modes
  - Interviewers to ‘help'

See Bucher, Keusch, de Viitis, Fausti, Inglese, van Tienoven, McCool, Struminskaya & Lugtig (2023) Smart Survey deliverable M6: review stage.

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2. Machine Learning

- Focus on Time Use and Household Budget
- Household Budget
  - Detecting receipt, judging picture is good enough
  - Using OCR to convert to text data
  - Separating tekst into shop, product, amount, price
  - Linking to Coicop
- Time Use
  - Using geolocation to populate an activity diary
  - Suggest activitities
    - Traveling, shopping, in restaurant, etc.

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3. UX, User Interaction

- Household Budget
  - Detecting receipt, judging picture is good enough
    - What to do if picture is not good enough?
  - Using OCR to convert to text data
    - What to do if conversion fails? Uncertainty about tekst?
  - Separating text into shop, product, amount, price
    - What to do with errors?
  - Linking to Coicop
    - What to do if no good linkage is there, or multiple ones?

4. Mode effects

- We know some respondents are ‘hard to get’ using apps
  - Need for secondary modes (web + mail)
- Break in time-series due to switch to smart survey

- In 2024 Experiments:
  - Mode selection and mode measurement effects
  - Different levels of smartness
    - With a lot of user involvement, or little

Recent smartphone-app pubs

See www.peterlugtig.com

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