Instituts thématiques Inserm
Institut national de la santé et de la recherche médicale

Institut Pierre Louis d'Épidémiologie et de Santé Publique
Pierre Louis Institute of Epidemiology and Public Health

SORBONNE UNIVERSITÉ
CRÉATEURS DE FUTURS DEPUIS 1257

Sensor and smartphone-based investigations of environmental effects on health

QuanTIM Webinar
SESSTIM UMR 1252
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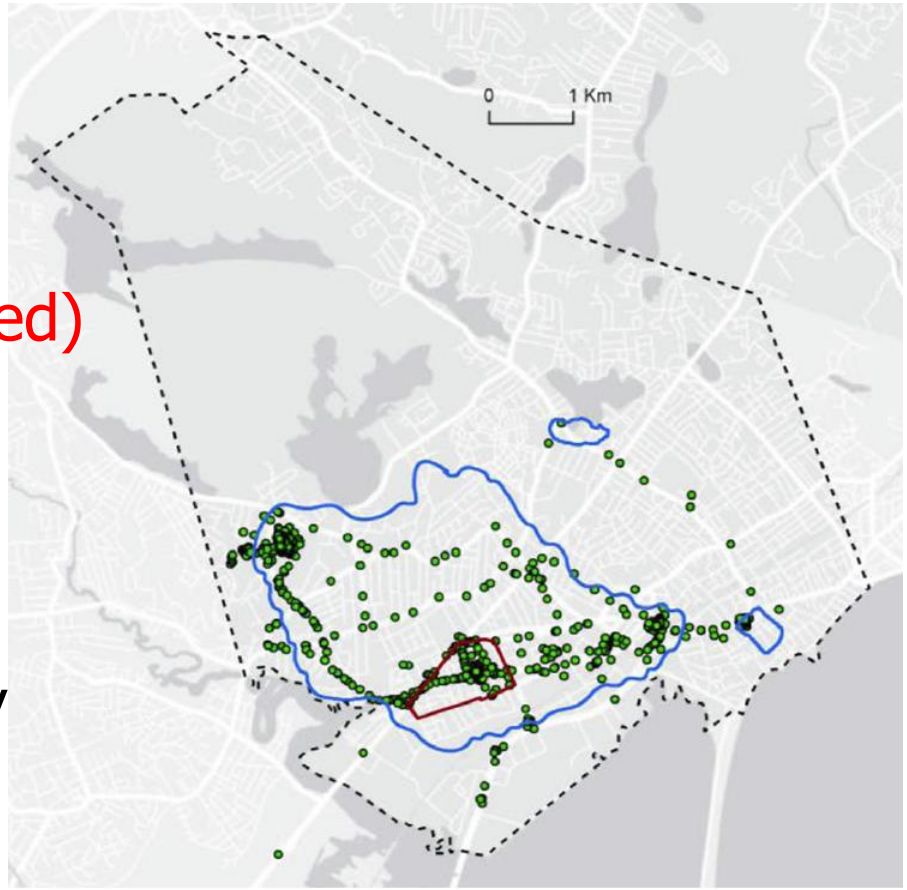
Basile Chaix
UMR-S 1136
Inserm – Sorbonne Université

Protocols based on GPS data (1)

Determination of the neighborhood with GPS data

- 32 US adolescents carried a GPS receiver and an accelerometer over 2 weeks
- GPS points (green) were used to compare the self-reported neighborhood (blue) to the administrative neighborhood (red)
- Participants spent more time in self-reported neighborhoods (80%) than in administrative neighborhoods (58%)
- They had more physical activity in these neighborhoods (14.7 min against 9.5 min) (even after adjustment for the size of neighborhoods)



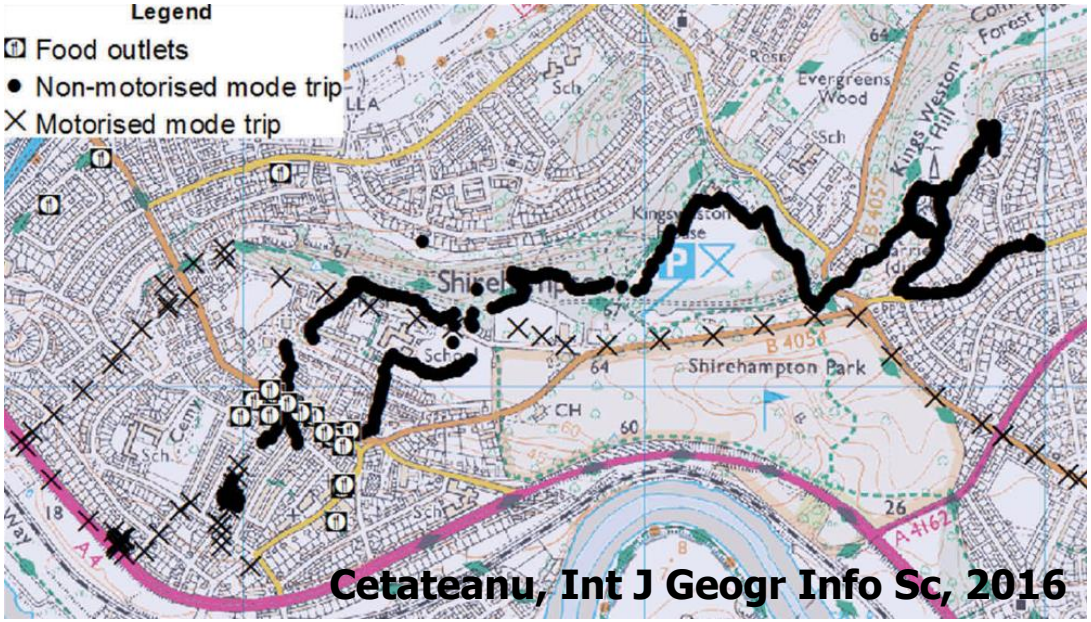
Robinson, IJHG 2013;12:57

Protocols based on GPS data (2)

Assess environmental exposures

During motorized travels, contacts with the environment are reduced

- Unsupervised algorithms to distinguish motorized from non-motorized trips
- Agreement of 88% on the mode in a manually classified sample of trips
- "The non-motorized exposure to the food environment" was not very different from the overall exposure for these urban children



Cetateanu, Int J Geogr Info Sc, 2016

Protocols based on GPS data (3)

Use of GPS receivers to measure behavior

- 135 children, 8-14 year old, in the USA; GPS data over 7 days
- Use of GPS data to measure behavior by overlapping them with a GIS: **>15 min in a park over 7 days**
- Distance to the closest park from the residence
- The use of a park was 4 times more frequent when the distance from the residence to the park decreased by 100 m, after adjustment

	Extended neighborhood park use (0: ≤15 minutes park use,1: >15 minutes within park)		
		Fully adjusted models	
Predictor variables	Single predictor model[a]	Single predictor model[b]	Multi- predictor model[b]
Park distance[c] (unit=100 m)	2.96 (1.47, 5.95)	4.11 (1.66, 10.18)	4.06 (1.61, 10.24)
Park greenness[d] (comparing 25th to 75th percentile)	1.31 (0.70, 2.46)	1.63 (0.72, 3.68)	2.12 (0.61, 7.31)
Park area[e]	1.00 (0.99, 1.00)	1.00 (0.99, 1.00)	0.99 (0.99, 1.00)
Number of parks[e]	1.36 (0.76, 2.43)	1.41 (0.66, 3.01)	1.18 (0.42, 3.30)

Dunton et al. Am J Prev Med 2014

Toward multisensor protocols (1)

Detection of body posture

Accelerometry

Behavior

Cigarette consumption

GPS receiver

Location

Smartphone surveys

Wearable cameras

Black carbon

Particles, gazes

Environmental exposures

Noise

Temperature Light

Radio-frequencies

Health

Ambulatory blood pressure

Blood pressure at rest

Heart rate variability

Electrodermal activity
Skin temperature

Spirometry

Impedance pneumography

Electro-encephalography

Current trends

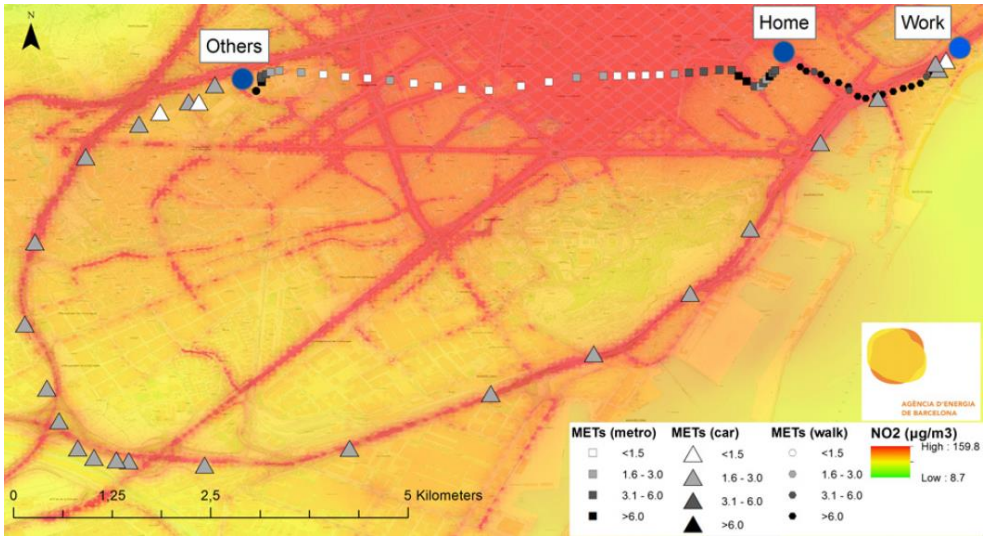
- multisensor devices
- miniaturization
- autonomy :
  - battery
  - memory
- Server communication

Toward multisensor protocols (2)

Measurement of exposures with a combination of sensors

Exposure to air pollution

- 36 participants in Barcelona carried a GPS and accelerometer
- Estimation of inhaled doses based on GPS location and energy expenditure
- The travel activity corresponded to 6% of the time of participants but to 11% of their exposure to NO_2 and to 24% of inhaled doses
- The difference in mean exposure between the GPS trajectory and the residence could be up to 50 µg/m^3



De Nazelle, Environmental Pollution 2013

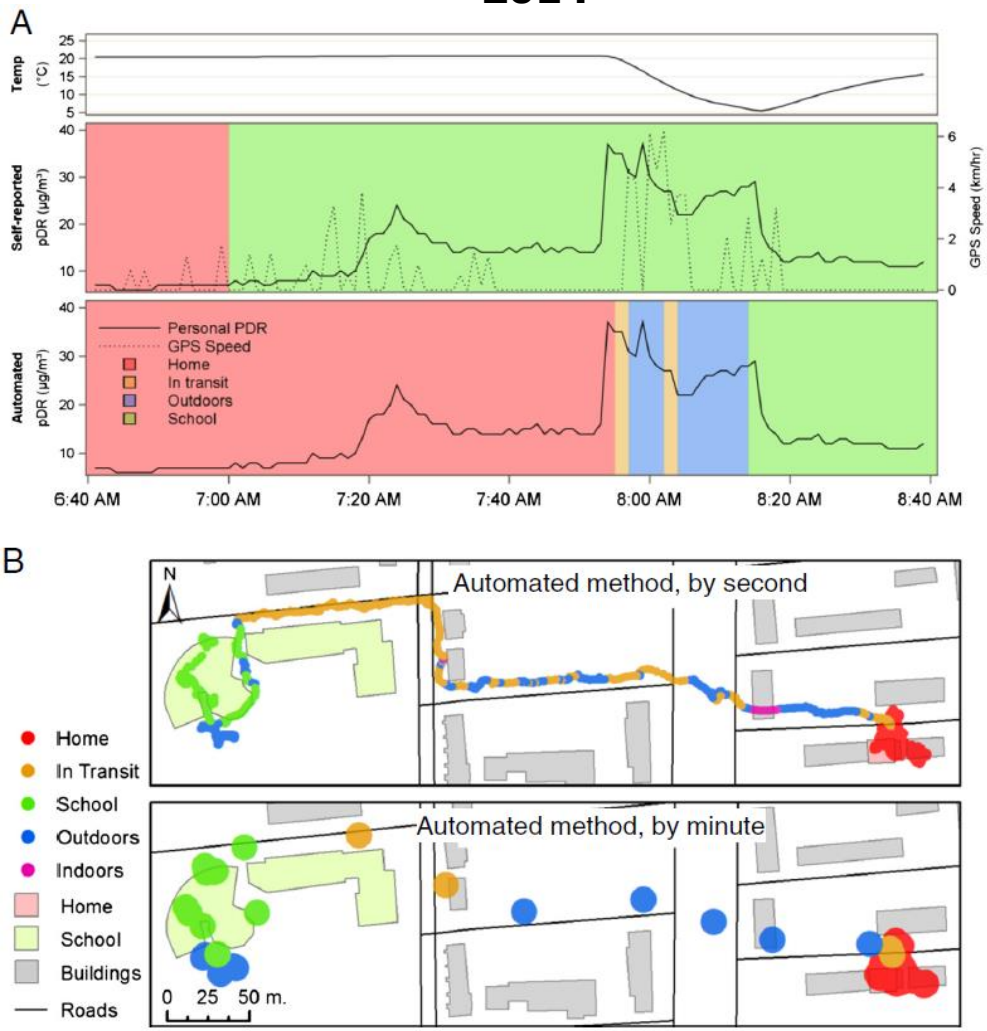
Toward multisensor protocols (3)

Measurement of exposures with a combination of sensors

Nethery, Environmental Health 2014

Exposure to air pollution

- 54 children in Montreal
- Activity / location:
  - reported in a diary for each period of 30 minutes
  - automatically classified with GPS and personal temperature data
- Measurement of the personal exposure to $PM_{2.5}$
- The exposure to $PM_{2.5}$ during trips was of 15.9 µg/m³ with the automatic classification and of 6.8 µg/m³ with the diary



Importance of prediction algorithms (1)

Expert rules, standard models, or machine learning to predict relevant dimensions from sensor data

- Travel behavior (trips, places visited, transport modes)

→ accelerometry, GPS receiver, heart rate

- Body posture (sitting, lying…) and activities (running, biking…)

→ combination of accelerometers, GPS receiver, etc.

- Energy expenditure

→ pedometer, accelerometer, barometer, altimeter, GPS receiver, gyroscope, magnetometer, heart rate, electrodermal activity, body temperature

- Minute ventilation (→ inhaled doses of air pollutants)

→ activity types, accelerometer, heart rate, breathing rate

- Time spent outdoor

→ GPS receiver, outdoor temperature

- Sleep duration, sleep quality

→ accelerometer, heart rate, electrodermal activity, electro-encephalography

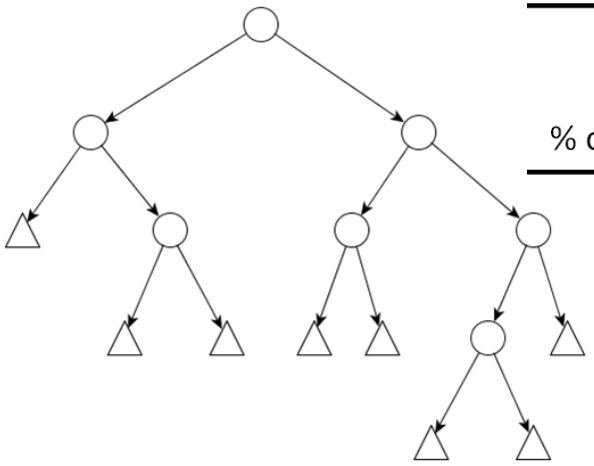
- Mood

→ heart rate, electro-encephalography, breathing rate, electrodermal activity, face analysis

Importance of prediction algorithms (2)

Prediction of transport modes

- 4 categories (walking, biking, driving, public transport)
- Based on random forests considering 170 predictors (GPS, accelerometry, GIS, and survey variables)



	Overall	Walking	Biking	Priv. Motor.	Public
% correct	**90.0**	95.3	54.0	89.7	82.8

⚠ Limitation: start and end points of trips must be known a priori

Brondeel & Chaix. Med Sci Sports Exerc 2015.

→ New all-in-one algorithm detecting trips and predicting modes: addition of heart rate, 1-minute windows, a posteriori homogenization

Rate of success of predictions:

91% for trips and places visited

80% for transport modes

Giri & Chaix. Int J Health Geogr

Importance of prediction algorithms (3)

Transport and physical activity

RECORD GPS Study
7138 trips
229 participants
Accelerometry over 7 days

→ **Prediction of physical activity in each trip**

Global Transport Survey (EGT)
82084 trips
21332 participants

→ **Probabilistic replacement of trips**

Definition of scenarios of change of mode in the EGT survey

Urban travel plan of Ile-de-France region (2010→2020)

- increase by 12% of the number of trips with public transport
- increase by 2.5% of the number of biking trips

Mean transport-related physical activity **19 min per day**
Urban travel plan **+1.9 min per day**

	Low education (no secondary)	Mid education (second., 2 years Univ.)	High education (≥3 years Univ.)
Urban Mobility Plan	+1.6 min	+1.9 min	+2.2 min

⚠ Potential increase of social inequalities in transport-related activity

Brondeel & Chaix. IJBNPA 2017.

Life-segment/momentary analysis (1)

Classical approach	Sensor-based life-segment approach
Reliance on **self-reported** data or external data as proxies	**Sensor-based measurement** of behaviors and exposures
Analyses with **individuals** as statistical units	Analyses with segments of **individuals' observation periods** as statistical units
Static and uniform exposure in residential neighborhoods = partial assessment	Assessment of **momentary exposures** in the multiple contexts visited
Overall health outcomes for an extended time (few time points)	**Space-time disaggregation** of the outcome (intensively repeated outcomes)
Crude analyses of behavior	Behaviors **contextualized** in their immediate environments
Fully / partly **cross-sectional** data	Analysis of **time sequences** (ordering of exposures, behaviors, and health states)
Standard regression analyses confounded, e.g., by preferences	**Case-crossover** analyses comparing each individual to herself/himself
Analysis of **individual and environmental** factors	Analysis of individual, environmental, and **situational** factors

Chaix. Annual Review of Public Health 2018.

Life-segment/momentary analysis (2)

Exposure to black carbon and blood pressure response

- MobiliSense Study

Exposure

Confounding factors



Outcome variable

- 6772 ambulatory blood pressure measurements for 245 participants

	SBP (mixed effect models)	DBP (mixed effect models)	SBP (fixed effect models)	DBP (fixed effect models)
Five minutes	0.57 (0.30, 0.83)	0.36 (0.14, 0.58)	0.42 (0.17, 0.67)	0.31 (0.09, 0.53)
Fifteen minutes	0.47 (0.17, 0.78)	0.36 (0.12, 0.60)	0.38 (0.09, 0.67)	0.31 (0.07, 0.55)
Thirty minutes	0.16 (-0.18, 0.49)	0.23 (-0.02, 0.48)	0.20 (-0.11, 0.51)	0.23 (-0.02, 0.48)
One hour	-0.02 (-0.41, 0.38)	0.08 (-0.21, 0.37)	0.03 (-0.32, 0.38)	0.12 (-0.15, 0.39)

Models adjusted for noise, physical activity, temperature, relative humidity, proportion of time spent at home or in motorized transport, week vs. weekend, living standard of place of measurement, and short-term time trend

Mixed models were additionally adjusted for residence area, age, sex, household income per member, education, employment, monthly alcohol consumption, body mass index, and living standard of residential area.

Bista & Chaix

Life-segment/momentary analysis (3)

Mixture of pollutants and the blood pressure response

- 3319 ambulatory measures of blood pressure for 221 participants
- A sixth sensor:

- Air pollutants: NO_2, NO, CO, O_3, black carbon, and $PM_{2.5}$
- Quantile G-computation to estimate the effect of the mixture
- Effect corresponding to a one-quartile increase of all the pollutants of the mixture

Bista & Chaix. Environ Res 2023

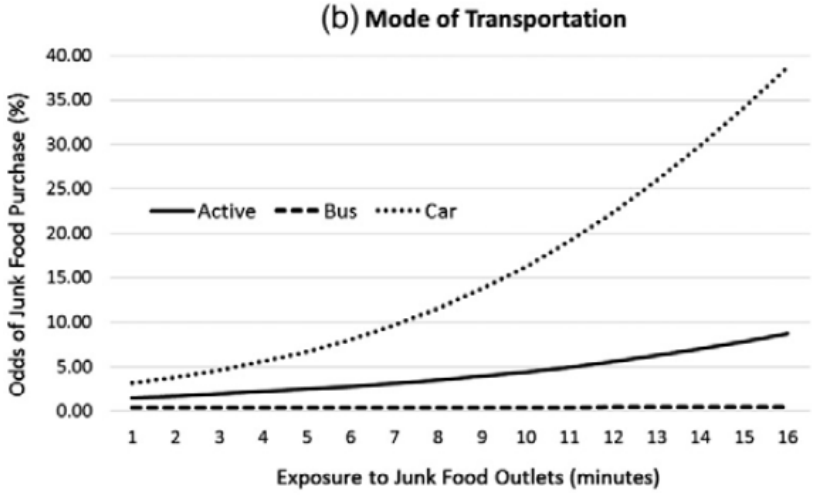
Air pollutants	β (weight) (systolic)	Mixture ψ (IC 95%) (systolic)	B (weight) (diastolic)	Mixture ψ (95% CI) (diastolic)
5 minutes				
NO_2	0.11 (5%)		0.28 (24%)	
NO	0.33 (16%)		-0.04 (6%)	
CO	-0.13 (100%)	1.92 (0.63, 3.20)	-0.66 (94%)	0.43 (-0.66, 1.52)
O_3	0.71 (35%)		0.32 (29%)	
BC	0.89 (44%)		0.53 (47%)	
15 minutes				
NO_2	0.07 (4%)		0.07 (8%)	
NO	0.18 (11%)		-0.07 (10%)	
CO	-0.02 (100%)	1.64 (0.38, 2.90)	-0.67 (90%)	-0.11 (-0.99, 1.22)
O_3	0.71 (43%)		0.24 (28%)	
BC	0.70 (32%)		0.55 (64%)	
30 minutes				
NO_2	0.21 (14%)		0.03 (4%)	
NO	0.08 (6%)		-0.25 (25%)	
CO	-0.27 (100%)	1.21 (-0.11, 2.53)	-0.74 (75%)	-0.17 (-1.30, 0.96)
O_3	0.63 (43%)		0.31 (37%)	
BC	0.55 (37%)		0.48 (59%)	
1 hour				
NO_2	0.40 (31%)		0.01 (8%)	
NO	0.08 (6%)		0.00 (0%)	
CO	-0.45 (100%)	0.83 (-0.44, 2.09)	-0.63 (100%)	-0.49 (-1.56, 0.58)
O_3	0.54 (42%)		0.07 (47%)	
BC	0.26 (20%)		0.06 (45%)	

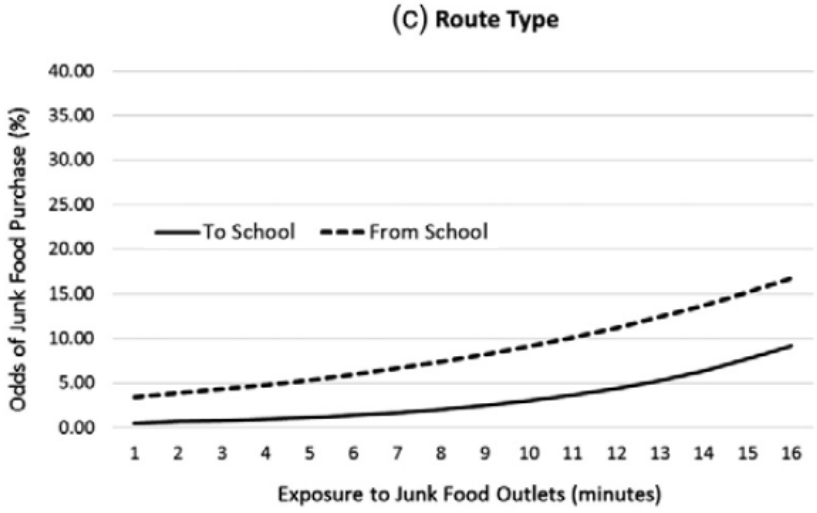
Models adjusted for physical activity, temperature, relative humidity, proportion of time spent at home or in motorized transport, week vs. weekend, living standard of residence and place of measurement, residence area, age, sex, household income, education, employment, monthly alcohol consumption and body mass index.

Life-segment/momentary analysis (4)

Momentary effects of food environments

- 654 children aged 9-13 years
- Outcome variable from the diary: food purchase on the home – school way (to and from school)
- Paths evaluated with GPS data
- Exposure: minutes spent within 50m of a junk food outlet
- Exposures and purchases merged at the trip level (n = 4588)
- Finding: Increase risk to purchase junk food in trips with a longer duration of exposure to junk food outlets





Sadler. Can J Public Health 2016

Ecological momentary assessment (1)

Passive sensors do not permit to capture all the relevant dimensions

- perceptions of the environment, intentions, affects, complex behaviors, etc.

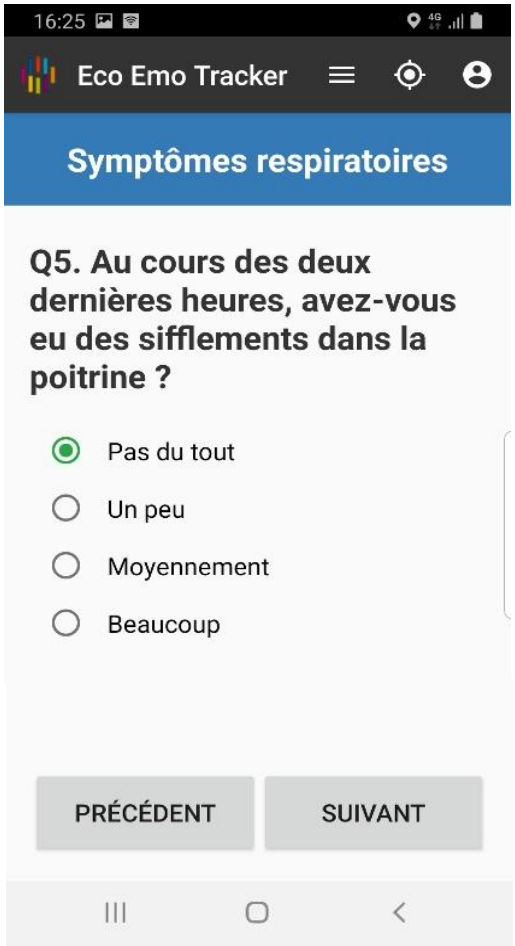
Ecological momentary assessment vs. traditional survey methods

- momentary rather than retrospective
- ecological (in situ) rather than out of context

Sampling of experience

- to improve measurement and causal inference
- critical to randomly select the time of surveys

Eco Emo Tracker



Ecological momentary assessment (2)

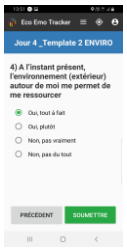
Server

Web application

Configuration
Follow-up

Eco Emo Tracker

Smartphone application



Triggers

When?
Condition?

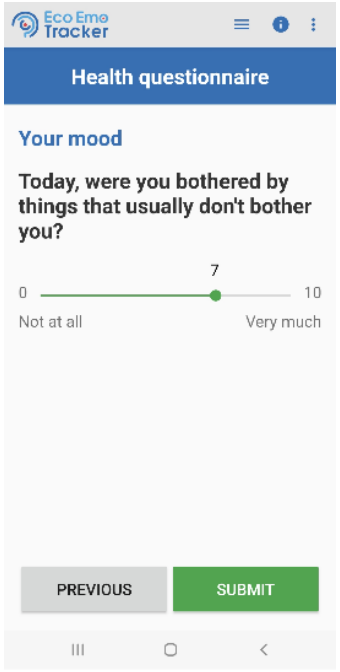
Forms

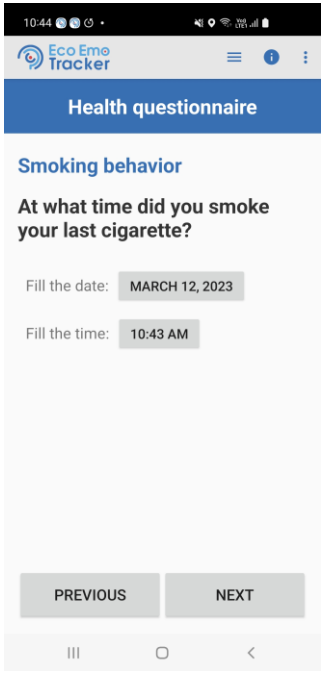
Phones

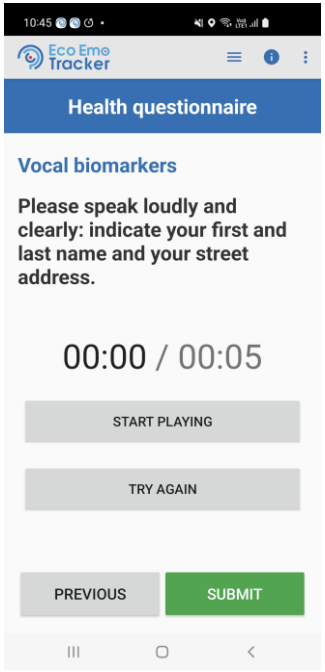
Ecological momentary assessment (3)

A variety of answer modes

- Check boxes and radio buttons
- Numerical value
- Slider bar
- Free text
- Hour and/or date
- Audio recording
- Picture

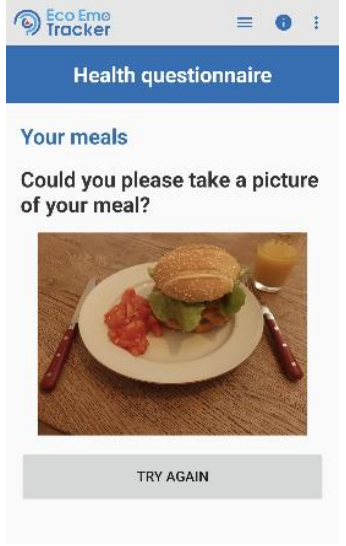






A variety of triggers

- Permanently available
- At fixed time
- At random time
- The participant is inside / outside
- The participant arrives to / leaves from a place or an area

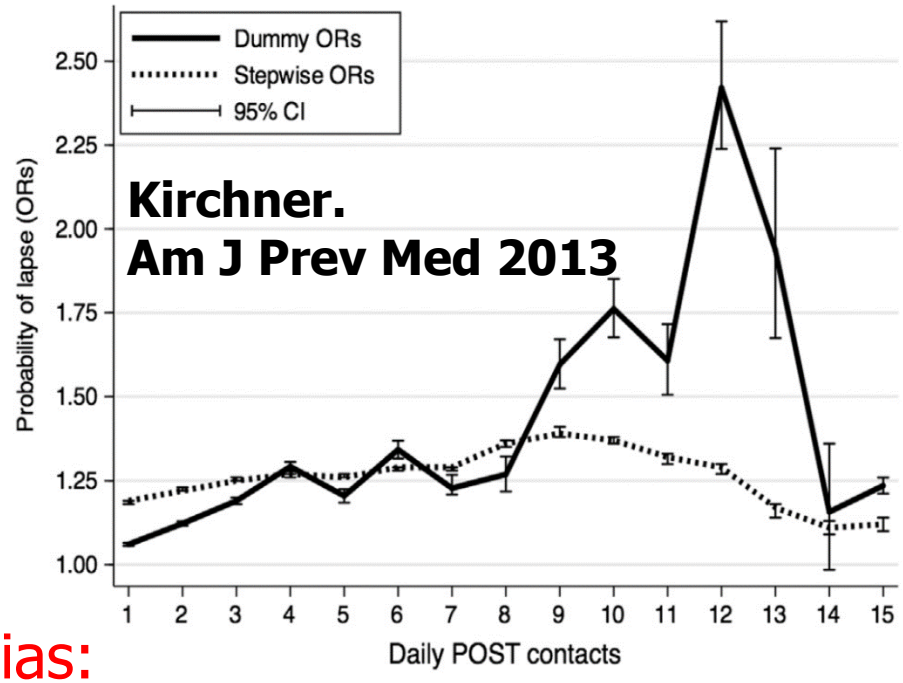


Background collection of GPS data

Geographic ecological momentary assessment (1)

Tobacco stores and tobacco consumption

- 475 US participants attempting to quit smoking
- Exposure to tobacco stores within 30 m of GPS points (every 15 min over 1 month)
- Consumption of tobacco assessed with an electronic momentary survey
- The risk of lapsing on a given day increased with the number of contacts with tobacco stores (OR = 1.07, 95% CI: 1.06 – 1.08)



Warning, risk of selective mobility bias:
The exposure to a store can relate to a visit to purchase tobacco.

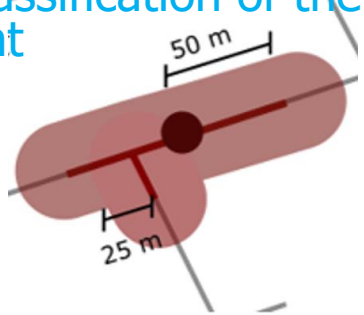
Geographic ecological momentary assessment (2)

Analysis among 216 participants > 60 years

- 4830 questionnaires over 7 days (22 / participant), 9689 questions
- CES-D depression questionnaire
- Measurement of environmental exposures over **2 hours before each questionnaire**, based on 1 082 047 GPS points;
- Distinction between indoor and outdoor points

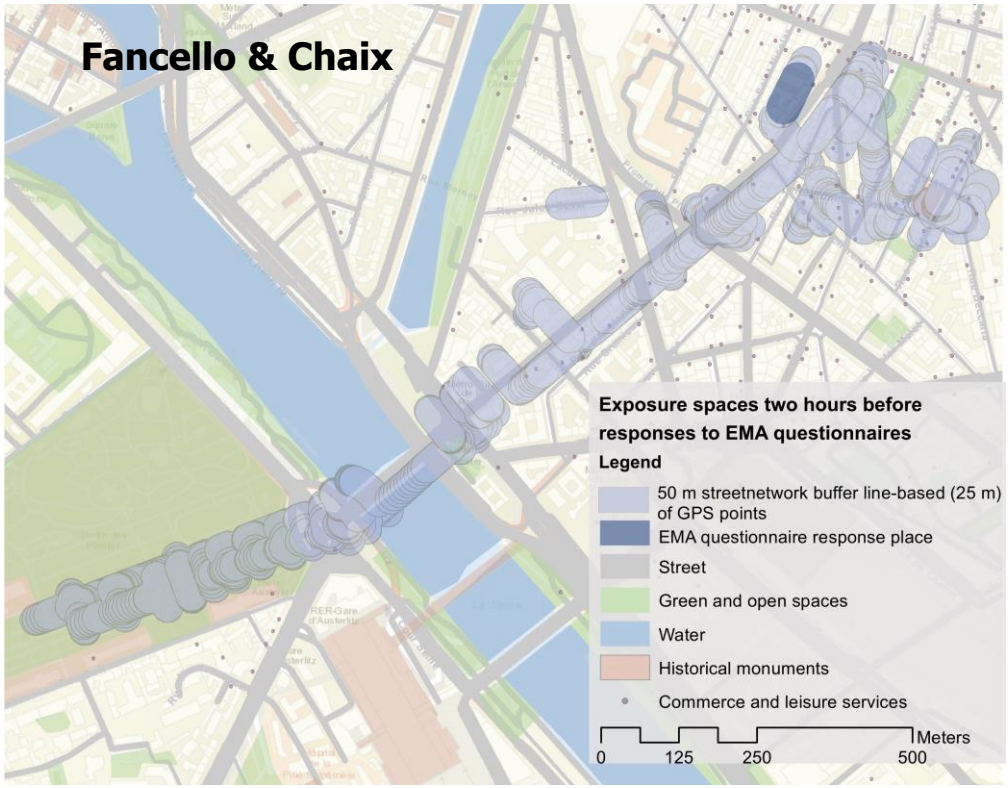
For each GPS point

- GPS point map matched
- Selection of street network within 50 m
- 25 m buffer
- Classification of the point



A question-naire and the 2 preceding hours

- GPS point buffers over the previous 2 hours
- Time (in hours) of exposure to specific environmental features



➔ **Time-weighted environmental exposures**

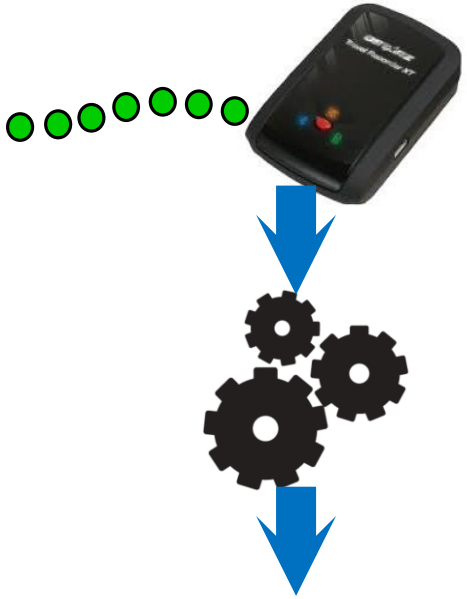
Geographic ecological momentary assessment (3)

Analysis of 216 participants, 4830 questionnaires, 9689 questions

- Outcome: CES-D scale 0–3, reverse coded so that higher score means better mental health
- Random effect at the day level and individual level
- Time autocorrelation accounted for
- Compared with individual level fixed effect analysis

	Between-person comparisons		Within-person comparisons	
	All points within 2 hours	Outdoor points within 2 hours	All points within 2 hours	Outdoor points within 2 hours
Green and open spaces				
Water elements	0.19 (0.05, 0.34)	0.88 (0.15, 1.88)	0.18 (0.01, 0.30)	0.91 (0.32, 2.24)
Architectural elements				
Services and culture	0.06 (0.00, 0.12)	0.19 (0.06, 0.32)	0.06 (-0.00, 0.11)	0.20 (0.07, 0.33)
Openness				
Walkable path		3.24 (0.22, 6.90)	0.26 (-0.01, 0.52)	3.01 (0.10, 6.35)
Noise pollution		0.03 (0.00, 0.07)		
Traffic				
Population density				
Ageing index				
Income				

GPS-based web mobility survey



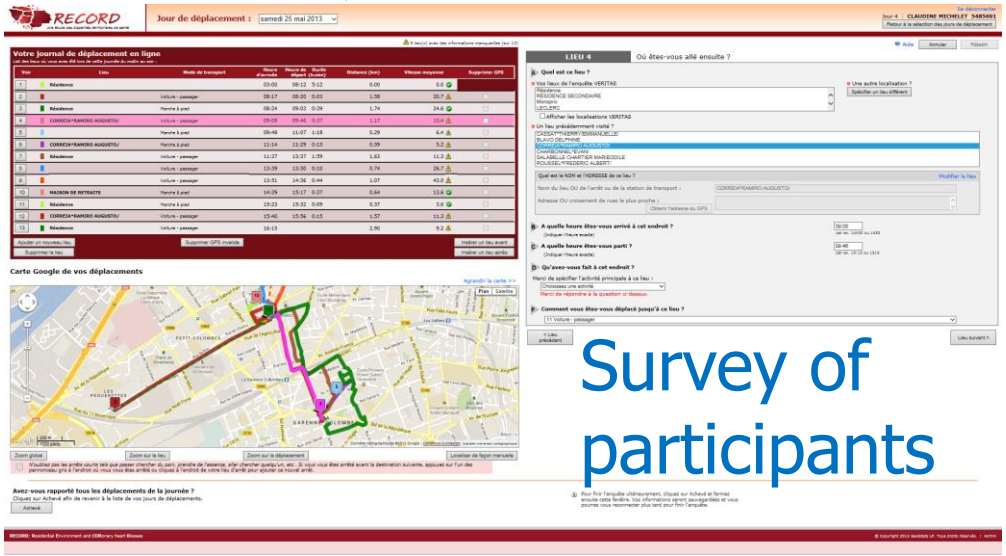
GPS receiver carried over 6 or 7 days

Automatic processing of GPS data

- Segmentation of tracks into trips, trip stages, and visited places
- Recognition of transport modes and activities at places

Activity schedule for p31 (June 12 2014)

	Start	End	Activity / mode
A1	00:00	07:32	Residence
T1 - 1	07:32	07:38	Walk
T1 - 2	07:38	08:15	Metro
T1 - 3	08:15	08:26	Walk
A2	08:26	12:15	Work
T2	12:15	12:19	Walk
A3	12:19	12:53	Restaurant
T3 - 1	12:53	12:57	Walk
T3 - 2	12:57	13:14	Bus
T3 - 3	13:14	13:16	Walk
A4	13:16	13:29	Clothing store
T4 - 1	13:29	13:32	Walk
T4 - 2	13:32	13:48	Bus
T4 - 3	13:48	13:52	Walk
A5	13:52	18:01	Work
T5 - 1	18:01	18:10	Walk
T5 - 2	18:10	18:50	Metro
T5 - 3	18:50	18:55	Walk
A6	18:55	23:59	Residence



Survey of participants

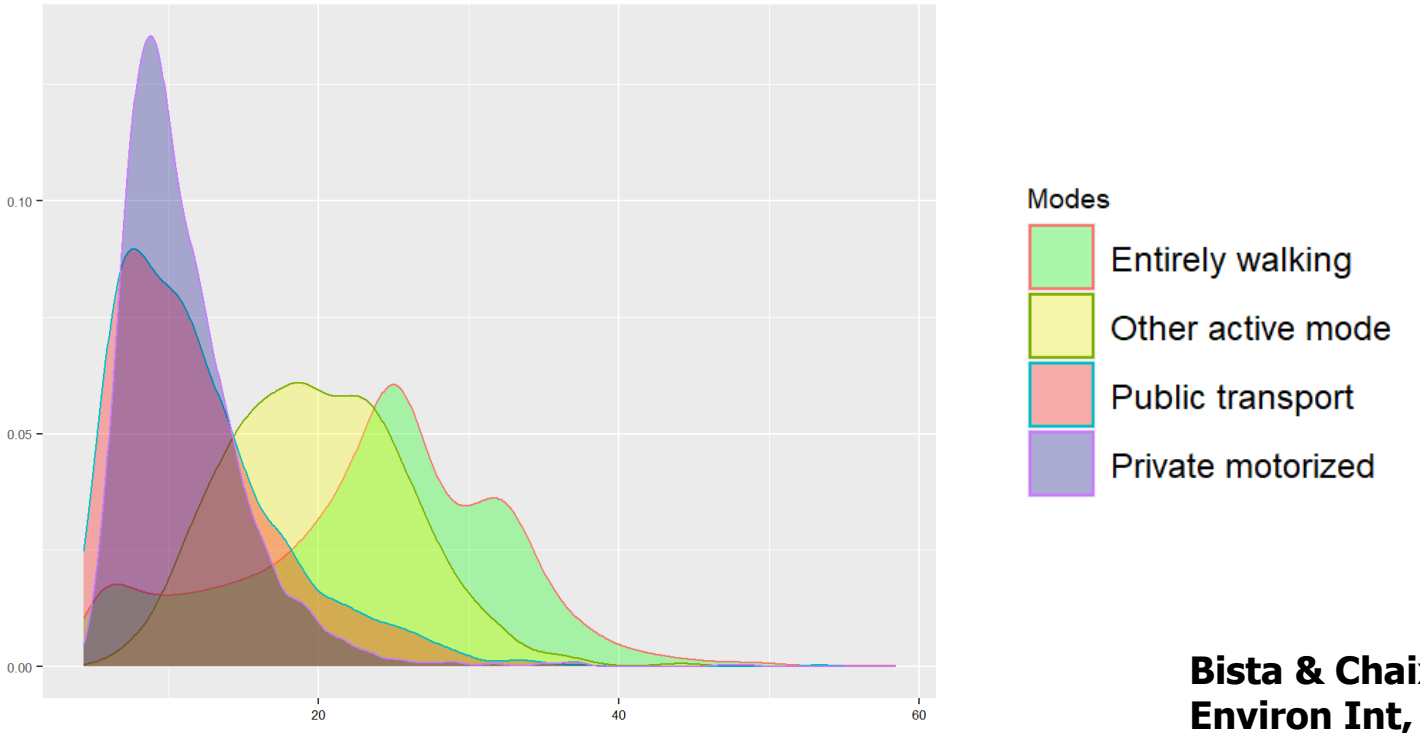
→ Patterns of use of time and space allowing us to contextualize the data of the other sensors

Mobility survey: application (1)

Analysis based on the MobiliSense data

- 7495 segments of trips (unique mode) for 283 participants
- Black carbon assessed with wearable AE51
- Inhalation based on minute ventilation predicted from accelerometry
- Linear multilevel model with random effect at individual level

Density of minute ventilation (L/min) by transport modes



Bista & Chaix, Environ Int, 2022

Mobility survey: application (2)

	Concentration (µg/m³)	Inhalation (µg per 30 min)
Entirely walked trips	Ref.	Ref.
Other active modes	1.03 (0.68, 1.38)	0.41 (0.25, 0.57)
Bus/coach	1.41 (0.99, 1.83)	-0.33 (-0.53, -0.13)
Metro	3.08 (2.82, 3.34)	0.06 (-0.06, 0.18)
Suburban train	1.53 (1.20, 1.86)	-0.63 (-0.79, -0.47)
Tramway	0.01 (-0.74, 0.76)	-0.94 (-1.29, -0.59)
Private motorized (driver)	2.31 (2.10, 2.52)	-0.20 (-0.30, -0.10)
Private motorized (pass.)	2.07 (1.73, 2.41)	-0.24 (-0.40, -0.08)

Multilevel linear model with a random effect at the individual level

Bista & Chaix, Environ Int, 2022

Models adjusted for season, day of week, hour of day, and the ambient concentration of PM2.5 and NO2 at the level of the GPS track (Airparif monitoring stations)

Mobility survey: application (3)

Analysis of MobiliSense data

- 7800 segments of trips (unique mode) for 282 participants
- Sound level assessed by frequency bands with SV 104A
- Distinction between overall sound level and levels for low frequency noise, intermediate frequency noise, and high frequency noise
- Linear model with random effect at the individual level and time autocorrelation function

	LAeqT (overall)	Low frequency	High frequency
Walking	Ref.	Ref.	Ref.
Other active	3.5 (2.4, 4.6)	5.7 (4.6, 6.9)	3.6 (2.6, 4.6)
Bus/Coach	2.7 (1.4, 4.0)	8.7 (7.4, 10.0)	2.2 (1.0, 3.4)
Metro	5.5 (4.7, 6.3)	6.0 (5.2, 6.8)	4.1 (3.3, 4.8)
RER/TER/SNCF	4.0 (3.0, 5.1)	5.5 (4.4, 6.6)	1.4 (0.5, 2.4)
Tram	2.3 (0.4, 4.2)	5.4 (3.4, 7.4)	-1.8 (-3.5, -0.1)
Personal motorized (driver)	2.2 (1.6, 2.8)	9.6 (8.9, 10.2)	-0.6 (-1.2, -0.0)
Personal motorized (passenger)	-0.3 (-1.5, 0.9)	6.4 (5.2, 7.6)	-3.3 (-4.3, -2.2)

Models were adjusted for: week vs. weekend, time of the day, age, sex, being in couple, education level, employment, and household income per member

Low, medium, and high frequency: 20Hz-125Hz, 160Hz-2kHz, 2.5kHz-20kHz

Wang & Chaix

Conclusions

Few take-home messages

- A new generation of environment – health studies:
  - follow-up with multiple sensors and smartphone surveys
  - pre-processing with algorithms
  - momentary exposures and health measures repeated at a high frequency
  - space-time structure of data accounted for
- Studies of short-term effects focusing on mechanisms
- Interaction between individual, environmental, and situational factors
- Interventional perspectives:
  - Urban and environmental interventions
  - Interventions aiming to provide to the right person the right amount of support at the right time in the right place (JITAIs, just-in-time adaptive interventions)