ANNUAL REVIEWS

Annual Review of Public Health

Mobile Sensing in Environmental Health and Neighborhood Research

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Annu. Rev. Public Health 2018. 39:367–84

The *Annual Review of Public Health* is online at publhealth.annualreviews.org

https://doi.org/10.1146/annurev-publhealth-040617-013731

Keywords

continuous monitoring, environment, mobility, neighborhoods, sensors, smartphones

Abstract

Public health research has witnessed a rapid development in the use of location, environmental, behavioral, and biophysical sensors that provide high-resolution objective time-stamped data. This burgeoning field is stimulated by the development of novel multisensor devices that collect data for an increasing number of channels and algorithms that predict relevant dimensions from one or several data channels. Global positioning system (GPS) tracking, which enables geographic momentary assessment, permits researchers to assess multiplace personal exposure areas and the algorithm-based identification of trips and places visited, eventually validated and complemented using a GPS-based mobility survey. These methods open a new space-time perspective that considers the full dynamic of residential and nonresidential momentary exposures; spatially and temporally disaggregates the behavioral and health outcomes, thus replacing them in their immediate environmental context; investigates complex time sequences; explores the interplay among individual, environmental, and situational predictors; performs life-segment analyses considering infraindividual statistical units using case-crossover models; and derives recommendations for just-in-time interventions.

THE CONCEPTUAL GROUNDS OF MOBILE SENSING IN PUBLIC HEALTH RESEARCH

Supplemental Material

Public health research has witnessed a rapid development in the use of wearable sensors, i.e., location, environmental, behavioral, and biophysical sensing devices that provide data at regular intervals. To develop a comprehensive overview of this literature (see **Figure 1** for a summary of concepts) and provide recommendations for future research (**Table 1**), a narrative review of this emerging literature was conducted. As detailed in **Supplemental Material 1**, this review focused on sensor-based studies in the field of public health (e.g., studies on physical activity, dietary behavior, addictions, mental health) that assessed environmental exposures using either global positioning system (GPS) data or a dedicated device; of particular interest were studies that combined several tools.

Mobile Sensing as a Source of Objective Data

Public health research has extensively used self-reported data from a posteriori questionnaires as proxies of the objective measurements that were lacking, e.g., for physical activity, sleep patterns, travel modes used, and regularly visited places. Self-reported data misclassify study participants to a significant extent, e.g., for physical activity and travel behavior (46, 80). A benefit of mobile sensing as an alternative source for these dimensions is to provide objective data to reduce misclassification.

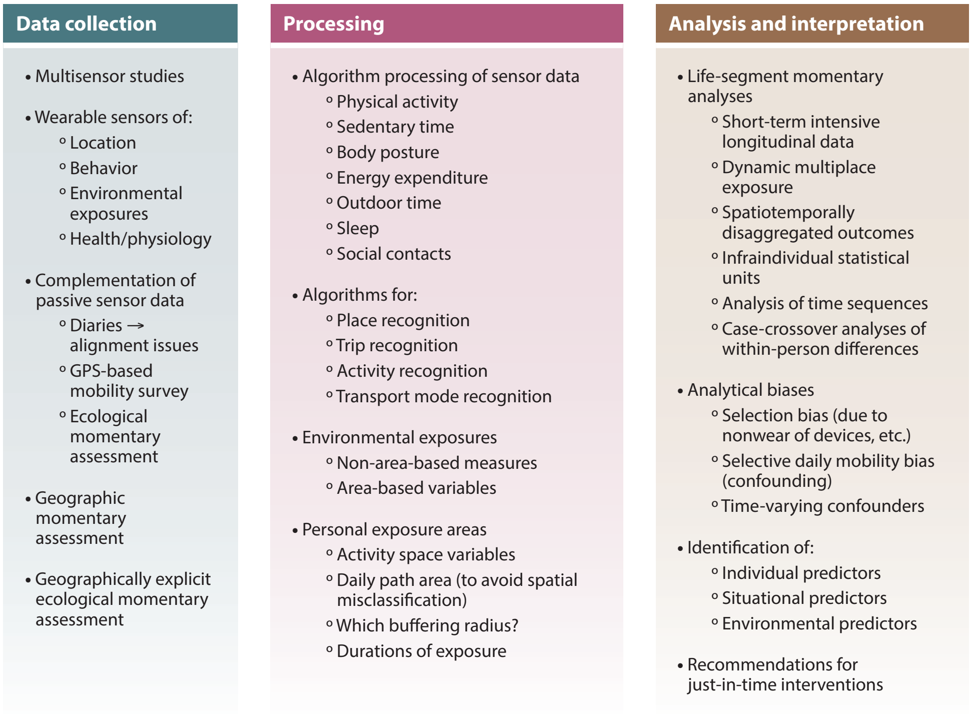

Figure 1

Overview of concepts related to sensor-based data collection protocols and related life-segment analyses for environment and health studies in public health.

Table 1 Recommendations and research agenda for the development of sensor-based momentary environmental studies in the field of public health

Domain	Recommendations
Regarding the theoretical bases of studies	The dramatic development of sensors conveys a risk of technology-driven research, which has to be addressed through the a priori development of sound hypotheses and through the critical assessment of whether each sensor and algorithm provides sufficiently reliable and valid data.
	Investigators will have to develop theoretical models that account for individual and environmental factors but also for situational factors and which take into account how the latter interact with the former, as relevant to the conception and implementation of fine-tuned intervention programs.
Regarding data collection	Studies should increasingly collect multiple channels of relevant time-stamped data by using separate devices and integrative multisensor devices (without altering the participants' behavior).
	Scholars will have to develop integrated protocols, including passive and active devices collecting data across most relevant domains, including location, environmental exposures, behaviors, psychology, and health status.
	Researchers will have to develop multiple strategies to disaggregate temporally and spatially the exposures but also the behavioral, psychological, and health outcomes, e.g., through passive sensing, GPS-based surveys, and EMA.
	Future research will benefit from additional studies that combine GPS receivers for exposure assessment with passive sensors other than classical accelerometers (e.g., advanced sensors for posture detection, biological sensors) and with EMA.
	To interpret data from passive sensors, researchers critically need detailed time-use information (on periods spent in trips and trip stages and at visited places). To accomplish this goal, I recommend performing GPS-based prompted recall web mapping surveys, although they are costly.
Regarding data preparation and data analysis	Efforts will be needed to develop sound measures of environmental exposures based on GPS tracks that take into account the activity context (e.g., measures of exposures based only on trip-related GPS points, specific to particular travel modes, distinguishing between outdoor and indoor locations).
	Using time-stamped GPS data, investigators will also have to account for the cumulated durations of exposures and identify the relevant induction periods.
	Such refined measures of exposures will have to be compared with more traditional variables and validated against perceptions of the corresponding exposures or relevant behavioral/health outcomes.
	Researchers will have to carefully adapt the GPS-based measures of exposures to mitigate the risk of selective daily mobility biases by modifying the spatial footprint (i.e., which places, which trips) used for exposure calculations.
	To fully correct selective daily mobility biases, scholars will have to assess which destinations were visited only because the previous or next one was visited (chain destinations) and to collect data on the premeditated versus incidental use of services.
	Rather than aggregating the sensor data only at the individual level, researchers are encouraged to also develop analytical designs that consider infraindividual statistical units and preferably meaningful units such as trips or stays at visited places.
	Researchers should take care to address at the analytical stage, or at least at the interpretational stage, the different forms of bias that threaten life-segment analyses, including residual confounding by time-varying confounders.
Regarding recommendations for interventions	When conceiving their sensor-based research protocols and implementing their life-segment analyses, researchers should develop recommendations of concrete just-in-time interventions that provide the right type and amount of support to the right person at the right time in the right place.

Abbreviations: EMA, ecological momentary assessment; GPS, global positioning system.

Moreover, relying on passive sensing makes it possible to dedicate questionnaires to dimensions whose measurement requires self-report (e.g., environmental perceptions, emotional states).

A New Space-Time Perspective in Public Health Research

Previous neighborhood and health literature has restrictively focused on residential environments (13, 14, 43, 51). Exclusively investigating residential neighborhood exposures implies a substantial misclassification of the total environmental exposure (18) [a phenomenon referred to as spatial misclassification (25)]. To move beyond this fragmented consideration of space, various strategies were developed to collect more detailed data on the various places visited by people across space and time. Whereas web mapping surveys of the regular places visited permit one to expand the exposure information collected along the spatial continuum (62), GPS tracking allows one to expand it also along the time continuum, yielding high-resolution space-time data (83).

I argue that the continuous monitoring of participants with wearable sensors sets the basis for a novel and complementary perspective for understanding human behavior and health in their environmental contexts (as summarized in **Figure 1**) (11, 45). This effort toward microspatial and temporal scales requires a shift in the driving theoretical models and analytical methodologies. Whereas classical studies are grounded in the abstract view of individuals connected to their residential neighborhoods without any time-use information available, these novel studies can identify the detailed succession of places visited over an observation period. While traditional studies therefore consider static and uniform exposures, this novel approach takes into account the full dynamic of exposures, analyzing momentary exposures (11) as an opportunity to operationalize the time–geography perspective (35). On the outcome side, whereas traditional studies often involve variables (e.g., self-reported) aggregating information over a relatively long period (45), mobile sensing studies can disaggregate spatially and temporally the dimensions of interest (11). As a consequence, there is a loose connection between contexts and behaviors or health outcomes in classical studies; in contrast, these new studies can contextualize behaviors and health states in their immediate environments (42). The classical approach focuses on individuals, comparing individual-level units through standard multilevel regression analyses, whereas these novel studies analyze a set of short monitoring periods or life segments for each individual, allowing each person to be compared with herself/himself.

The ability to correlate time-stamped information from various sensors leads to the development of short-term effect studies exploring dynamics at a microtemporal scale. Although these studies cannot directly identify the medium- or long-term predictors of diseases, they are well suited to investigate the contexts of behaviors and the immediate determinants of acute health/behavioral responses as a pathway to chronic effects on health.

These high space-time granularity data offer the opportunity to test novel hypotheses at an unprecedentedly fine scale (45), e.g., on the environmental triggers of behavior. Also, complex time sequences of phenomena (temporal ordering of exposures, situations, behaviors, and health states) can be analyzed to uncover the genesis of behavior or transient health states (immediate precipitants, chains of phenomena). For example, associations between environmental factors and blood glucose have been investigated at the population level with individuals as statistical units, but the day-to-day human–environment interactions, behavioral choices, and life events that cause blood glucose to fluctuate remain unexplored (21).

Environmental, Situational, and Individual Factors

One reason why novel hypotheses can be tested is that sensor-based momentary studies allow investigators to take into account situational factors, in addition to the more commonly considered individual and environmental factors. Individual and environmental characteristics are relatively permanent factors connected to individuals or environments in a more or less intrinsic way. Conversely, situational factors refer to transient circumstances in space and time that are more or less contingent for the individual and environment visited. Examples of situational characteristics include the hour of the day, the day of the week, and the season; the weather; the number and nature of persons present around ego and their type of interactions with ego; the particular reason for being in a place and the type of activity in which ego is engaged; the transient mood and emotional state of ego; the recent history of ego (e.g., activities over the previous hours).

Situational factors have received much consideration in alcohol and drug addiction research, as obvious determinants of these behaviors (32). Their assessment through objective measurement strategies should allow them to be systematically investigated as independent factors or modifiers of individual/environmental influences. Accounting for situational factors is particularly relevant to the development of just-in-time interventions (56), as alluded below.

DATA COLLECTION AND PROCESSING: EMERGING PRACTICES

The Toolkit of Sensors and Related Challenges

The toolkit of sensors employed in public health and epidemiologic studies comprises a growing set of devices, allowing researchers to measure various aspects of the "external exposome" (54).

A growing number of sensing opportunities. **Figure 2** reports examples of wearable sensors categorized into three domains: behavioral sensors, environmental sensors, and physiological and health sensors. Details on these sensors and bibliographic references are provided in **Supplemental Material 2**.

Supplemental Material

Other tools collect data pertaining to several of these domains of information. For example, pictures from wearable cameras have been used to assess the environments visited [e.g., parks (57), presence of food (73) or alcohol (17) marketing signs] and behaviors [e.g., dietary behavior (58), the types of children's destinations (16), sedentary behaviors (50), or travel durations (48)]. However, the resulting images are burdensome to convert into usable information in the absence of efficient image-processing algorithms.

Various devices or systems of devices collect several channels of data, either from a unique type or from differing types of sensors. For example, the VitaMove system collects data from several accelerometers placed on different parts of the body, e.g., on the trunk and on the thigh, allowing the detection of body postures (7). Other examples of multisensor devices include the SenseDoc, which combines a GPS receiver and an accelerometer; the BioPatch, which records triaxial accelerations, heart rate, and respiratory rate; the multisensor board, which senses accelerometry, barometric pressure, humidity, temperature, light, audio, and GPS (42); and the Personal Air Quality Monitor, which integrates, in addition to sensors of gazes and concentrations of particles by particle size, a GPS receiver, an accelerometer, and a basic sound pressure monitor.

Smartphones also incorporate various embedded sensors (57). Moreover, they are programmable; have large touch screens; are able to link to external devices through wireless connections (and thus can serve as a hub for managing multiple streams of data); are able to transmit data to distant servers; have remote monitoring capabilities, powerful processors, and large amounts of memory; and are familiar to a growing fraction of the population (22). However, battery life remains an issue when simultaneously using several functionalities of the smartphone (23).

The challenges for manufacturers and researchers. Among the challenges faced by hardware developers, one key issue is the miniaturization of sensors, which is critical when asking participants

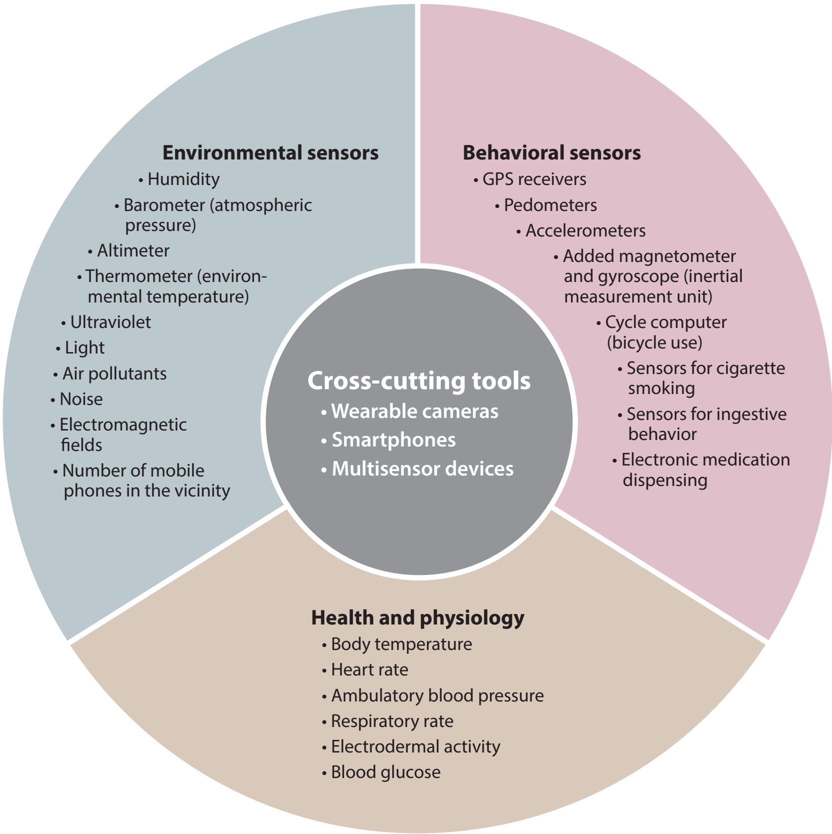

Figure 2

Examples of environmental, behavioral, and health and physiological sensors for public health research.

to carry several sensors. A second issue is the autonomy of sensor devices, in relation to both battery life and memory size. The durability of consumables (e.g., stickers to fix devices on the body, electrodes, filters for air pollution monitors) is also important. A third issue is the ability of sensors to transmit their data to central servers, e.g., through SIM cards integrated in the device, through Bluetooth communication with a smartphone, or using a Wi-Fi connection (57). The continuous transmission of data during the data collection period allows researchers to monitor the compliance of participants and the current status of the device (i.e., working or not) to address data collection problems (21). Moreover, if all data in their detailed format can be automatically uploaded to the servers (which might be infeasible or induce high transfer costs), such real-time transmission eases investigators' access to the data and reduces the risk of data loss during the collection and download phases. In addition to reducing the cost of sensors, a final challenge is to improve the operability of devices, which all have different cables or card readers and software for accessing the data. The automatic upload and integration of numerous streams of data in a unified computer platform (42) remain a relatively medium-term target, as experienced in the RECORD MultiSensor study (28) and other multisensor studies (57).

Challenges faced by researchers include the many decisions to be made for the configuration of each sensor and processing of its data (49, 81), the choice of the monitoring period length to capture the patterns of interest (41), and the field strategies to deploy to minimize behavioral reactivity (83) (alteration of a person's behavior due to the burden of devices or social desirability bias) or to reduce dropout (strategies may include support from staff, financial incentives, feedback to participants, etc.). Another issue, in addition to assessing the performance of sensing in each domain, is to determine the maximum number of sensors or burden that participants can accept (57), which depends on the type of sensors and other aspects of the protocol and on the characteristics and motivation of participants (e.g., patients or not). Another important challenge for the future of sensor-based data collections is to better grasp the respective benefits of intensive studies over a well-defined number of days compared with less controlled and less intensive data collections over longer periods of time (e.g., with a smartphone over several months) (44).

GPS Tracking in Public Health Research

Compared with the declarative data obtained from travel surveys or diaries (13), GPS receivers provide objective time-stamped location data (49) with limited burden on participants (18). In most circumstances, the positional error of GPS receivers is small compared with the buffer radiuses selected for exposure assessment.

Geographic momentary assessment. In allowing researchers to work with time-indexed geographic coordinates (45) and to replicate a person's space-time path (22), GPS receivers open a new research era of geographic momentary assessment (52). Geographic momentary assessment has several key benefits: (*a*) It permits investigators to link the various locations visited throughout the day with environmental factors, providing an accurate accounting of the person–place dynamics (52) and environmental conditions to which individuals are exposed (environmental characterization) (21); (*b*) it allows investigators to focus on the transport behavior as a source of physical activity, air pollution and noise exposures, stress, etc.; and (*c*) it provides a basis for assessing the time use, activity patterns, and space-time budgets of study participants.

The automatic identification of places visited, trips, activities, and transport modes. In many GPS-based studies, researchers process GPS points without information on whether they correspond to a visited place or to a trip and without information on transport modes. Such data have limitations, both for understanding behaviors and for environmental exposure assessment.

Certain studies have relied on a manual identification of trips through a visual inspection of GPS data in a geographic information system. For example, some studies manually isolated trips to and from school (37, 74). Other studies manually extracted information on home–work trips in adults (19, 59). To reduce the burden of data processing, other studies have applied automatic algorithms (*a*) for the recognition of places visited and resulting assessment of trips between them, (*b*) for the assessment of particular places or trips, and (*c*) for the recognition of travel modes.

Regarding the identification of places and trips, certain studies have used a cluster detection algorithm to detect stationary places (38), whereas other have relied on a definition of stops as aggregates of successive GPS points within a certain spatial range lasting for a minimum duration and with speeds below a certain threshold (47). Another study developed a complex algorithm based on kernel density estimation to identify the places visited (corresponding to elevated densities of GPS points possibly generated through multiple visits to the place) (12, 76).

Regarding the assessment of visits to specific places, a study attributed clusters of successive GPS points to very specific types of facilities (e.g., athletic facility, entertainment facility, green space, religious facility, restaurant, retail) using geographic information system data without any confirmation from participants (64). Another study assumed that participants visited a fast-food restaurant in the case of spatial concordance for a certain duration between the participants'

GPS location and the corresponding service identified in a geographic information system (70). Without confirmation from participants, this approach [also followed in other studies (47)] is risky and probably insufficiently accurate, e.g., in settings where services are located on the ground floor of buildings also used for other functions or where various services are located very close to each other. Studies also attempted to identify specific trips automatically, such as home–school trips (20), for example as trips that started and ended within 40 meters of home and school (38). Similarly, another study identified the transport activity of children during leisure time (79), a construct that would be difficult to self-report.

Some of the GPS-based algorithms that identify places visited and trips also retrieve the transport modes used in trips (55). The Personal Activity Location Measurement System (PALMS) (8) has been used in the largest number of studies in the field of public health. The Moves smartphone application is also an option. As reviewed elsewhere (10, 71), algorithms for mode recognition can be classified into criteria-based approaches [involving somewhat debatable expert rules, such as cutoffs applied to speed (20)] and machine-learning approaches. The latter are subdivided into supervised and unsupervised methods (10). Supervised methods first derive a prediction model from a data set of trips with known modes (from manual classification or participants' reports), which is then used to predict modes in another data set (4, 31). Heterogeneity in the generation model between the training and the target samples would lead to misclassification. Such models have been developed to predict modes either at the trip level (4) or for small windows of, for example, 1 minute (where a posteriori smoothing is then needed to mitigate incoherent switching between different modes) (29). Unsupervised methods do not need a database of trips with preclassified modes. Rather, considering that the different motorized and nonmotorized modes each have their own distribution of speeds, they attempt to classify the trips into modal categories on the basis of the distribution of speeds in each trip segment, removing the need for manual labeling (10, 53).

Most transport mode recognition algorithms rely only on GPS data, whereas some have combined GPS and accelerometer data (4). One study identified trip modes from GPS, accelerometer, and heart rate data; however, investigators used a visual and manual approach rather than an algorithmic approach (61).

Strategies to complement GPS tracks. It is useful to have data on activities at places and transport modes to address specific questions, improve the definition of exposures, and address inferential problems. However, the previous section makes it clear that the automatic assessment of activities and modes suffers from misclassification. To obtain reliable data, participants' self-reported information (69) or validation is needed.

A first option is to rely on a separate paper or electronic diary (69). Some studies have a posteriori linked information on travel modes self-reported in a diary to trips identified from GPS or accelerometer data (19, 59). However, the real-time reporting of information on activities and modes is burdensome, and a study based on a trip diary over two days showed that the reported data were already of lower quality on the second day (1). Additionally, one challenge is that the two separate sources of data on the same trips, the GPS data and the diary data, must be aligned, which implies approximations. A study reported that the mode was assigned to a bout of activity in the case of temporal overlap and/or time proximity (68). In another study that matched diary-reported visits to fast-food restaurants or supermarkets with the corresponding GPS-based visit, allowing a tolerance of plus or minus 10 minutes or 30 minutes significantly improved the rate of matching (69).

To reduce misclassification, a different approach developed in the transport research field involves GPS-based web mapping mobility surveys. GPS data are uploaded into a Web application that integrates algorithms for processing them and mapping functionalities for displaying the preanalyzed GPS tracks; on this basis, participants are asked to validate, correct, and complement information on the types of places visited and travel modes (2, 3, 75, 82). This approach is also referred to as prompted recall surveys because the preanalyzed GPS tracks are used to stimulate participants' recall. In the RECORD GPS/MultiSensor Studies and MobiliSense project, I use one of the most advanced applications to date: (*a*) It segments GPS tracks into visited places, trips, and unimodal trip stages; (*b*) it recognizes the places visited from previously reported participants' regular destinations and general points of interest; (*c*) it imputes travel modes from GPS speeds, self-reported use of transit, and geographic data on transit stops; (*d*) it allows investigators to import transit trip itineraries and times from the General Transit Feed Specification data; and (*e*) it includes a number of tools for manually editing the GPS tracks (retrieving short stops, segmenting tracks to create a stop, manual drawing, imputation of street-network itineraries). We use this tool to derive an accurate schedule of the personal activities and trips over several days, with edited GPS tracks cleaned from the residual artifacts that would preclude the calculation of distances; with start and end times of each visit to places, trip, and trip stage; and with validated information on activities and transport modes. These accurate spatialized time use data are costly to derive but provide a powerful basis for interpreting the time-stamped data of other sensors. Map-based prompted recall survey tools can also collect complementary data, e.g., on the social network contacts involved in activities/trips (23) or on physical activity bouts identified from accelerometry data (5, 55).

Personal Exposure Area Variables

Wearable sensors capture a range of environmental exposures (57), leading to non-area-based measures of environmental exposure. The present section focuses on area-based variables of exposures that build on location-aware technologies such as GPS receivers. GPS-based variables, or environmental variables along the daily path area, have been suggested as a way to operationalize the notion of activity space (24, 25). Activity spaces relate to the places visited by people during their daily activities and to the routes between these places (13). Strong discordances have been reported between residential and GPS-based variables of exposures (25, 67). Differences in exposure have been reported even between the modeled shortest paths and the actual GPS paths (37).

There are many options, and hence decisions to make, to determine the spatial footprint used for exposure assessment (13, 15, 24) (i.e., the exact area or polyline used for extracting exposure data prior to the calculation). Using area delimitations that do not reflect the true exposure area leads to spatial misclassification (25), as an important component of the overall misclassification of exposures (other sources corresponding to the time of exposure and to the exposure data themselves).

A preliminary choice to make is whether to use the crude GPS data, filtered GPS data, or edited and complemented GPS tracks. Then, a buffering strategy must be selected. Buffering the GPS points or the GPS track polyline will lead to slightly different exposure areas if GPS sampling is relatively sparse. Selecting a radius is no easy task. When assessing the potential access to services, very short radiuses should be retained if the aim is to capture the range of sight within urban contexts to represent a viewshed [e.g., 50 or 100 meters] (67, 70)], whereas larger ones (e.g., half mile) (18, 85) could be used if considering that the subject could modify her/his itinerary on the basis of knowledge of proximate opportunities. When assessing environmental exposures, whereas relatively large radiuses around the home are used for residential measures to account for the unobserved patterns of movement around the residence, GPS-based measures can rely on short radiuses, for example corresponding to the viewshed [e.g., to assess the exposure to built environment factors with a buffer width of 100 meters (38)], or even extract exposure values along the track (for air pollution and noise exposures).

A strategy to refine exposure assessment is to distinguish between different stages of GPS tracks, e.g., during trips versus at a visited place, outdoors versus indoors, or according to the type of visited place or transport mode. Investigators can use adaptive radiuses, e.g., shorter for trips than for visited places or varying in width according to the type of visited place (62). Related strategies are to ignore episodes in motorized transport where contact with the environment is reduced to assess the nonmotorized exposure to the food environment (10) or the spatial accessibility only in pedestrian and bicycling activity spaces (40), or to estimate exposure effects separately for each transport mode (66). Another emerging improvement is to explicitly account for time durations, e.g., by assessing the cumulated duration (66) or percentage of time (10) spent near a source of exposure.

Exposure variables are becoming more algorithm-based. To make sure that these refinements are relevant, researchers should assess whether, compared with the more rudimentary variables, the novel ones better predict (*a*) perceptions of the corresponding exposures or (*b*) behavioral/health outcomes. Finally, it should be noted that few studies have used GPS data to define not the exposure but the behavioral outcome (e.g., contextualized physical activity) (26, 77, 84).

Sensor-Based Behavioral Variables

Algorithmic processing of sensor data also provides relevant information on behaviors of interest in public health. Behavioral dimensions predicted from sensor data include travel behavior, physical activity and sedentary time, body posture, energy expenditure, time spent outdoors, sleep, and interactions with social contacts, as briefly reviewed in **Supplemental Material 3**. These dimensions are inferred through algorithms that apply to one unique channel of data or to several channels from different sensors.

Supplemental Material

Ecological Momentary Assessment

It is often important to complement the objective information provided by wearable sensors with subjective information that can be obtained only by interacting with the participants (22). The usual self-report strategy involves retrospective (after-the-fact) assessments and takes a global perspective averaging information over a recall period (83). However, retrospective recall often differs from reality (32, 52), leading to differential measurement error.

As a survey strategy, ecological momentary assessment (EMA) (72) aims to attenuate recall error and memory distortion (22, 32). Its first key characteristic, the momentary component, is to assess current states in as close to real time as possible, when feelings are fresh (22). The second key element is the ecological dimension: Survey items are answered in situ to assess the ongoing experience of participants within its environmental context (22, 30, 52, 72, 83). The third characteristic of EMA is to sample repeated life segments to capture changes in experience in short time frames (22, 83).

EMA is typically useful to collect information on emotional status or mood (57); on experiences, intentions, and decisions; on specific aspects of behavior that cannot be objectively assessed; on accompanying persons (32); on other situational characteristics; on environmental perceptions [subjective account of the ecological context (52)]; and on aspects of the environment that cannot be characterized with sensors or geographic information systems.

Compared with paper diaries, the use of electronic devices such as smartphones or tablets extends the range of options for administering questionnaires. The strengths of electronic devices for EMA include the ability to manage complex administration schedules; the availability of prompting through buzzing and audio alarms (including recall prompts when a survey was missed); the option to propose interactive voice response surveys (32) or even open-ended questions to which participants respond through recorded audio messages (22) in addition to text surveys; and the possibility to perform certain data quality checks.

Modern EMA research uses a wide range of prompting strategies. Participants can be prompted at a given time, at regular intervals, or at random times within time slots [signal contingent responding (83)]. Self-initiated reporting is also possible (63) [event-contingent responding (83)]. More complex prompting strategies, referred to as sensor-informed context-sensitive EMA (27, 78), rely on the internal sensors of the smartphone and possibly on external data (e.g., geographic data) available to the triggering algorithm (52). Questionnaires can be generated when the participant arrives at home (if the application has access to coordinates for home), when the participant is in a green space (57) (if geographic data can be processed), after the smartphone accelerometer detects an episode of physical activity (27), when the participant is exposed to an environmental nuisance [e.g., to radiofrequency electromagnetic fields (78)], etc.

An emerging field combines EMA with geographic momentary assessment (i.e., GPS tracking), which is designated as geographically explicit EMA (52) or as integration of EMA with activity space analysis (32). Only very few studies have combined passive geographic tracking with interactive survey strategies to collect geolocated self-reported behavioral or perceptual data (22, 32) and to link momentary experience to objective environmental contexts in place and time (52). For example, one study correlated exposures to audit-based social and physical disorder within GPS tracks with self-reports of drug craving (30).

ANALYTICAL AND INTERPRETATIONAL CHALLENGES IN MOMENTARY INVESTIGATIONS

Life-Segment and Momentary Analytical Design

A number of sensor-based studies collected repeated outcome data for each participant (e.g., accelerometer physical activity, travel modes in trips) but aggregated data in an individual-level outcome before establishing correlations with GPS-based built environment exposures also aggregated at the individual level (33) or with residential neighborhood variables (36). Other studies of this kind collected outcome data at the individual level [e.g., current or usual dietary intake or food purchasing unrelated to the GPS wear period (18, 70, 85)], and thus they had to aggregate the GPS-based exposure at the individual level. Individual-level analyses of these data may occasionally be subject to the "individual aggregation fallacy" (an equivalent of the ecological fallacy that led to the development of multilevel/contextual analysis): For example, the consumption of less-healthy food by people who are exposed to fast-food restaurants more often does not imply that this unhealthy food consumption occurs after exposure to, and as the result of being exposed to, fast-food restaurants.

Certain sensor-based studies correlated exposure and outcome data at an infraindividual level. At a relatively aggregated level, some studies analyzed behavioral outcomes derived from sensors or diaries at the day level (with days nested within individuals) (60). At a finer grain, many studies (especially the descriptive physical activity location studies) analyzed data at the level of GPS data points/accelerometry epochs (9). Although readily available, these extremely short analytical units may not be ideal for behavior analysis because behavioral choices are made for longer time episodes (14). Trips and trip stages or stays at visited places are probably more meaningful analytical units for investigating physical activity or some other behaviors. Only very few studies could perform trip-level analyses of sensor-based outcomes, including physical activity studies that disaggregated the travel mode outcome at the trip level (11, 12, 38) and including one study that disaggregated a food consumption/purchasing outcome at the trip level (adolescents' junk-food purchasing in home–school trips) (66). Another strategy was to analyze physical activity intensity (derived from combined accelerometry and heart rate monitoring) in short 1-minute epochs but to take into account the nesting of these periods within identified trips (19). Other relevant periods of observation that have been used as repeated within-individual statistical units include physical activity bouts (34) or outdoor episodes (65). Finally, momentary analytical studies also include the approach that combines GPS-based geographic momentary assessment with EMA to investigate the immediate residential or nonresidential determinants of affective, perceptual, or behavioral self-reports (30).

These studies may indicate one of the paths to follow toward the future of environment and behavior sciences or environmental health sciences. The conceptual benefit of a space-time disaggregation of data (including the outcome) includes the ability to investigate the dynamic processes interrelating places visited, events, experiences, behaviors, and health status and the moment-to-moment influences involved in these cascades of phenomena (52, 83). With this approach, investigators can analyze between-person differences in health behaviors and health and their determinants as commonly done in traditional individual-level multilevel studies, but also within-person differences, i.e., why a given individual behaves in a different way or exhibits a different health status than he/she does at a different moment owing to changes in current and preceding situational and environmental factors (83). A strength of the latter approach is to neutralize, through the exclusive comparison of each participant to herself or himself in exposed and unexposed circumstances (52), confounding by stable individual preferences and attitudes. Such a case-crossover analytical approach has been applied very rarely to date to sensor-based data in public health studies (11).

From Short-Term to Longer-Term Influences

Studies involving continuous monitoring with sensors are well suited to investigate short-term responses to exposures. Short-term emotional or health responses are often transient and do not have a public health significance per se, but they might be important from a mechanistic point of view, as stimulations regularly repeated over a long period are often the basis for the chronicization of health effects. Still, empirically demonstrating whether and how such short-term influences lead to more permanent effects would be important. Thus, an aim for future research would be to reconcile studies of short-term effects and longer-term effects.

An appropriate design to address this goal is to conduct repeated sensor-based assessments over multiple waves, e.g., every six months or every year. It would allow researchers to investigate the impact of longer-term environmental exposures on changes in health status over two or several waves. Moreover, as a potential pathway for longer-term effects, this design would make it possible to explore whether the relationship between an environmental exposure and the short-term health response increases from one wave to the next as evidence of increasing sensitivity over time.

Analytical Biases in Sensor-Based Short-Term Effect Studies

Because of the burden of sensor-based protocols, participants can drop out from the study or have missing portions of repeated observations. If study dropout or missing data are determined by the exposure or by a determinant of the exposure and by the outcome or a determinant of the outcome, then selection biases can distort the association of interest. Such biases can alter associations estimated from between-individual but also within-individual comparisons (including when estimated with case-crossover analysis).

Regarding confounding, associations based on within-individual comparisons are threatened by time-varying confounders, for example momentary physical activity when assessing the relationship between ambient noise or stressful social interactions and blood pressure (behavioral confounder) or as another example the type of activity or accompanying persons when investigating the relationship between place characteristics and well-being (situational confounders).

Moreover, selective daily mobility biases are a major source of confounding for life-segment and momentary investigations, particularly when assessing the effect of environmental resources and other contextual factors on behavior. As described previously (13, 14), the structure of the bias is related (*a*) to the fact that the willingness to conduct an activity causally influences both the visit to places relevant to this activity (exposure) and the practice of the activity (outcome) during the follow-up; and (*b*) to the fact that investigators also calculate the spatial accessibility to environmental resources or contexts from these intentionally visited places (which the participant would not have visited if he/she had no intention to conduct the activity). A version of this bias is found in studies of the relationship between the spatial accessibility to or location in green spaces and physical activity (14) because the GPS-based so-called "accessibility" is also calculated from green spaces specifically visited to exercise where the participant would otherwise not have been. Another example relates to studies that correlated the GPS accessibility to food outlets with dietary consumption or food purchasing (18, 66, 67, 70), where the so-called "exposure" is, in fact, a mix of exposure and behavior. Considering three successive destinations (A, B, and C) and assuming that destination B was specifically visited to conduct the behavior, a way to correct this bias may be to exclude destination B and to replace the trips to and from destination B by the shortest street network itinerary between A and C when calculating environmental exposures. Such a correction would be valid only if the visit to the service was premeditated but would do more harm than good if it was incidental (i.e., visual exposure cuing spontaneous use), in which case the shortest network itinerary between A and C is more likely to pass through B anyway. Moreover, calculating exposures from destinations A and C would lead to bias if one of those was visited just because destination B was visited (to conduct the behavior); in that case, A and/or C would also have to be removed.

Another example of selective daily mobility bias in studies assessing the effects of environmental characteristics on travel mode choice or related outcomes is to calculate environmental exposures along the trip itinerary because the exact itinerary that was followed is itself determined by the chosen mode. Such bias may be mitigated by calculating the exposures, instead, along the recalculated shortest street network itinerary. A study comparing the actual routes assessed with GPS receivers with the calculated shortest routes did not find evidence of selective daily mobility bias (6). This is likely because the association examined (between the built environment and body mass index) implies a much larger causal distance than that in our example (where the outcome is the travel mode used): Environmental conditions around a chosen itinerary tell much more about the chosen mode than about the participant's body mass index.

CONCLUDING REMARKS: RECOMMENDATIONS FOR FUTURE RESEARCH

As one attempt to develop a research agenda, **Table 1** summarizes a number of recommendations for the full integration of mobile sensing in future environmental health and neighborhood and health research. The aim is to set the base of a life-segment epidemiology grounded in the continuous monitoring of participants with multiple sensors, investigating how momentary environmental exposures and situational factors influence health behaviors and health states through cascades of events, experiences, and affects. These recommendations pertain to the novel theoretical models needed to support this work, to the multisensor data collection protocols that have to be developed, and to the processing and analysis of these intensive longitudinal data.

Ultimately, the aim of this sensor-based environmental research is to generate knowledge on how to create a variety of places (45) and situations that provide optimal environments for healthy living for each individual profile. The methodology outlined in the present review provides a path for the development of just-in-time adaptive interventions (themselves based on mobile and sensing technologies), also referred to as ecological momentary interventions (39). These approaches are designed to provide the right type/amount of support at the right time in the right place for the right person (temporal, ecological, and individual sensitivity) by adapting to an individual's changing internal and contextual states (56).

DISCLOSURE STATEMENT

The author is not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

ACKNOWLEDGMENTS

This article has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement 647000, 2014 ERC Consolidator grant, MobiliSense project); from the European Union Horizon 2020 Programme [grant agreement 667661, Promoting Mental Wellbeing in the Ageing Population (MINDMAP)]; and from ANR (French National Research Agency, grant agreement ANR-15-CE36-0005-02, HANC project).

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