Advances and challenges in sensor-based research in mobility, health, and place

Eun-Kyeong Kim, Lindsey Conrow, Christina Röcke, Basile Chaix, Robert Weibel, Camille Perchoux

Advances and Challenges in Sensor-based Research in Mobility, Health, and Place

Eun-Kyeong Kim[1, 2, 3], Lindsey Conrow[4], Christina Röcke[3, 5], Basile Chaix[6], Robert Weibel[2, 3], Camille Perchoux[1]

[1]Department of Urban Development and Mobility, Luxembourg Institute of Socio-Economic Research (LISER), Esch-sur-Alzette, Luxembourg

[2]Department of Geography, University of Zurich, Zurich, Switzerland

[3]University Research Priority Program (URPP) Dynamics of Healthy Aging, University of Zurich, Zurich, Switzerland

[4]Department of Geography, University of Canterbury, New Zealand

[5]Center for Gerontology, University of Zurich, Zurich, Switzerland

[6] Sorbonne Université, INSERM, Institut Pierre Louis d'Épidémiologie et de Santé Publique, Nemesis research team, Paris, France

Correspondence should be addressed to: Eun-Kyeong Kim, Ph.D.

Department of Geography, University of Zurich, Zurich, Switzerland;

Department of Urban Development and Mobility, Luxembourg Institute of Socio-Economic Research (LISER), 11 porte des Sciences, L-4366, Esch-sur-Alzette, Luxembourg.

Email: eun-kyeong.kim@geo.uzh.ch; eun-kyeong.kim@liser.lu

Funding

Eun-Kyeong Kim was funded by the Velux Stiftung (Project No. 1155; Project acronym: MOBITEC-GP; Principal investigator: PD Dr. Timo Hinrichs). Funders had no role in organizing the special issue, executing the review research, and writing the manuscript.

Camille Perchoux was funded by the European Union, under the Horizon European Research Council (ERC) Starting grant program (Grant Agreement No. 101040492; Project acronym: FragMent). Views and opinions expressed are, however, those of the author(s) only and do not necessarily reflect those of the European Union or the European Research Council Executive Agency. Neither the European Union nor the granting authority can be held responsible for them.

Author contributions

EKK, CP, LC, CR, RW, and BC organized the special issue and conceptualized the study. EKK led the research and wrote the first version of the manuscript. CP, LC, and CR contributed to writing parts of the draft manuscript. EKK, CP, and LC discussed the structure and contents of the draft manuscript in depth. All authors revised and approved the final version of the manuscript.

Abstract

Mobile sensing using portable sensors and momentary assessments has transformed the way mobility and place are considered in health and well-being research. Research at the intersection of *Mobility, Health, and Place* has increasingly leveraged methodological advances in data collection using mobile sensing technologies, data processing, data analytics, and clinical applications to observe and unveil intertwined relations between individuals' characteristics and behaviors, changing environments, and their health and well-being at fine-grained spatial and temporal scales. In this editorial, we provide an overview of recent health and behavioral research in the context of mobility and place. Specifically, we classify health-relatable mobile sensing technologies with a proposed taxonomy of mobile sensing, and review how new sensing approaches transformed research trends in the field of mobility, health, and place. We then discuss challenges in data collection and processing, analysis, and interpretation and practices.

Highlights

- Mobile sensing has transformed research in *Mobility, Health, and Place*.
- It enables pervasive real-life measurements of personal behavior, context and health.
- It enables the development of novel digital biomarkers and personalized intervention.
- Classification of mobile sensing technologies and methods is proposed.
- Issues remain in data collection and analysis to address uncertainties and biases.

Advances and Challenges in Sensor-based Research in Mobility, Health, and Place

1. Background

Humans move from one place to another to fulfill their needs to survive and flourish in their living environments. Daily mobility, places we interact with, and daily activities affect our health and lifestyle behaviors, and vice versa. Research in *Mobility, Health, and Place* has increasingly employed mobile sensing, thanks to methodological advances in sensor-based technologies, study protocols, data collection methods, emerging (big and open) data sources, data processing and analysis, and development to clinical applications. People's wide adoption and daily use of mobile devices and smart gear has accelerated its application in research and clinics across the world; 81% of North American adults used smartphones and 21% of Americans used a smart/fitness tracker in 2019 (Sim, 2019; Vogels, 2020). The personal mobile sensing approaches have complemented, and sometimes substituted, more traditional research practices employing self-reports, interviews, tests, or in-lab assessments, and enabled innovative studies on physical, mental, and behavioral health, in relation to personal, social, and environmental contexts at both individual and population levels (Chaix, 2018; Sim, 2019).

These new approaches have brought novel concepts and terminologies in health-related and medical disciplines as listed in Table A1. We take the term of *mobile sensing* from Chaix (2018) to embrace both portable sensors and momentary assessments in real-life health and well-being contexts. *Portable sensors* are defined by Birenboim et al. (2021) as an umbrella term for comprehensive mobile, wearable, wireless sensor technologies. *Momentary assessments* emphasize frequently repeated surveys and functional assessments, on top of sensor-based data collection, in real-time using portable instruments (Shiffman et al., 2008).

In this special issue, we exhibit a collection of urban health studies that applied mobile sensing approaches to various topics on built environment intervention for population health inequalities (Fuller et al., 2021), activities and physical health in exposure to urban extreme heat (Zhao et al., 2021), comparison of exposure measures accounting for uncertainties in mobility behaviors and environments (Jankowska et al., 2021), comparison of spatial exposure estimation methods for the study of outdoor food and beverage advertising (Wray et al., 2021), comparison of exposure and mobility behavior measures based on travel path selection and transport modes (Klein et al., 2021), and the effect of regionally targeted lockdown measures for infectious disease using mobile-phone-based mobility data (Long et al., 2021). These studies cover physical health, health-related behaviors, and well-being under the influences of natural (Zhao et al., 2021) and built (Fuller et al., 2021; Wray et al., 2021) environments and health policies (Long et al., 2021). Three studies primarily focused on methodological advances in exposure (Jankowska et al., 2021; Klein et al., 2021; Wray et al., 2021).

In this editorial, we provide an overview of recent health and behavioral research in the mobility and place context. Specifically, we classify health-relatable mobile sensing technologies (Section 2), discuss how new sensing approaches transformed research trends in the field of mobility, health, and place (Section 3), and then discuss challenges in data collection and processing (Section 4), analysis (Section 5), and interpretation and practices (Section 6).

2. Taxonomy of Mobile Sensing

Classification of mobile sensing instruments. Mobile sensing is conducted with a variety of portable sensors and momentary assessment tools (Birenboim et al., 2021; Chaix, 2018). Considering technical modalities and practices in use, mobile sensing techniques can be classified by (1) the manner of interaction between a participant and a sensing instrument, (2) target features of observation or assessment, (3) sensing capacities and limitations, and (4) body-instrument relations.

Interaction between a participant and a sensing instrument. There are three types of sensing by participant engagement: (a) passive sensors, (b) active sensing, and (c) functional assessments, operationally conceptualized by Sim (2019) (Table *1*. Classification of mobile sensing instrumentsTable 1). In *passive sensing*, a participant's status or activity is passively observed without active responses or manipulation—e.g., location tracking via Global Positioning System (GPS), step counting via pedometer in a fitness wristband. While the passive sensors collect data in real time without the participant's manipulation, the participant is responsible for carrying a device and charging its battery regularly. *Active sensing* requires a participant to self-report perceived states and activities through (geographic) ecological momentary assessments ([G]EMA) (e.g., momentary map-based self-reports on a smartphone). A smartphone application (app) is commonly used for spontaneous or periodic self-reporting, thanks to near-ubiquity of smartphones and established mobile survey apps (e.g., movisensXS used in Röcke et al., 2022). The mobile apps prompt a user to report their current states (e.g., mood) or perceived environmental exposures (e.g., noise) via momentary questionnaires (Chaix, 2018), fill in electronic travel/activity diaries, or participate in personalized consulting with a chatbot. For *functional assessments* with sensors, a participant is instructed to self-conduct a functional test (e.g., 6-minute walk test), an instructed task (e.g., voice recording task) or a clinical measurement possibly using a medical kit (e.g., blood test kit) or device.

Observing features by a sensing instrument. Portable sensors can be categorized by their observing features including: (i) location, (ii) motion, (iii) proximity or contact, (iv) physiological states, (v) psychological/cognitive status, (vi) non-mobility health-related behaviors, and (vii) person-centered environment (Table *1*. Classification of mobile sensing instrumentsTable 1). First, regarding location sensors, GPS today is the most used location aware technology. By combining wireless telecommunication infrastructures such as Wi-Fi, Bluetooth (BT), cell tower networks, and passive infrared indoor sensors, more accurate and comprehensive location tracking is possible. Wi-Fi positioning and cell tower trilateration can augment the accuracy for both outdoor and indoor environments at where GPS signals are weak or lost (e.g., urban canyons, indoors). BT networks might be used to detect a proximal position of a person via Bluetooth tokens installed in built and mobile infrastructure (e.g., rooms, train carriages). Second, motion sensing plays a key role in recognizing physical movements and further activity types and intensity. Motion sensing is typically conducted with an Inertial Measurement Unit (IMU) that involves multiple motion sensors such as accelerometer, gyroscope, and/or magnetometer and allows calculating velocity, orientation and/or position. Other sensors (e.g., video, foot pressure sensor) can also monitor physical activities. Third, BT technology can be used to detect short-range proximity or in-person contacts between people, while location sensors measure more long-range proximity. An audio recorder has been used to detect conversational interactions with other persons. Fourth, some sensors collect physiological condition or response data (e.g., heartrate, body temperature, blood oxygen, blood glucose, and perspiration). Fifth, psychological and emotional status can be not only inferred by physiological sensors (e.g., electrodermal activity) but also observed by behavioral sensors (e.g., eye movement, facial muscle reactivity, voice variations). Sixth, behavioral sensors can capture health-related behaviors (e.g., smoking, eating). Finally, many portable environment sensors enable assessing person-centered environmental and social exposure including air quality, micro-atmosphere, noise, radio frequencies, light, visual stimuli, human voice, and floating population (Poom et al., 2021).

In active sensing, many features of personal health, behaviors, and environments, that are observed by passive sensors, can also be self-reported by a participant through reporting instruments. The potential features for self-reports include psychological and emotional states (e.g., subjective well-being, positive/negative affect, mind-wandering), physical health (e.g., fatigue), health behaviors (e.g., sleeping, drinking, exercise), daily activities (e.g., activity type, transport modes, accompanied people), environments (e.g., place type).

Functional assessments target objectively measurable features mainly for physical and cognitive abilities as well as physiological states through self-conducted tests and measurements. One typical physical ability test is a walk test via a GPS/IMU-enabled mobile app; mobile device users can self-initiate the measurement for outdoor walking activities. Cognitive tests (e.g., memory testing) have been implemented on mobile apps. With portable medical kits and devices, clinical measurements can be self-conducted more frequently including infectious disease diagnostics (e.g., COVID-19 antigen test) and blood pressure monitoring (e.g., portable blood pressure monitor).

Sensing capacities and limitations. Each sensing instrument has different measurement capacities by its technical nature and practical use. Light-weight portable/wearable sensors have limited observational duration, frequency, and spatial range, due to limited data storage, battery, and sensing mechanism, in which they are often in tradeoff relationships—e.g., sampling frequency vs. duration under limited memory and storage. The maximum spatial extent of measurement often depends on an instrument's sensing mechanism—e.g., GPS (worldwide), Wi-Fi (long-range), BT (short-range) (Seneviratne et al., 2017). Hence, device limitations dictate the maximum capacity and spatiotemporal extent of measurement. Simultaneously, measurement interval and duration in practical use are determined based on traits of observing phenomena and sampling strategy. Sensors with relatively higher sampling frequency (e.g., GPS, heartrate monitor) measure more regularly, but push notifications for self-reports from GEMA apps are often random in time to avoid potential bias occurring with fixed time of day (Röcke et al., 2022).

Body-instrument relations. Each portable sensing instrument has different relations with one's body. Body-instrument relationships can be defined by sensor intrusiveness and placement. *In vivo sensors* are sensors implanted under skin, which is more intrusive than *dermal sensors* that are worn (e.g., fitness tracker accessories) (Olla & Shimskey, 2015). Different body parts can be equipped with sensing devices (e.g., wrist, waist, chest, head, knee, foot) and sensor placement can affect comparability between studies and activity recognition performance (e.g., Allahbakhshi et al., 2019, 2020).

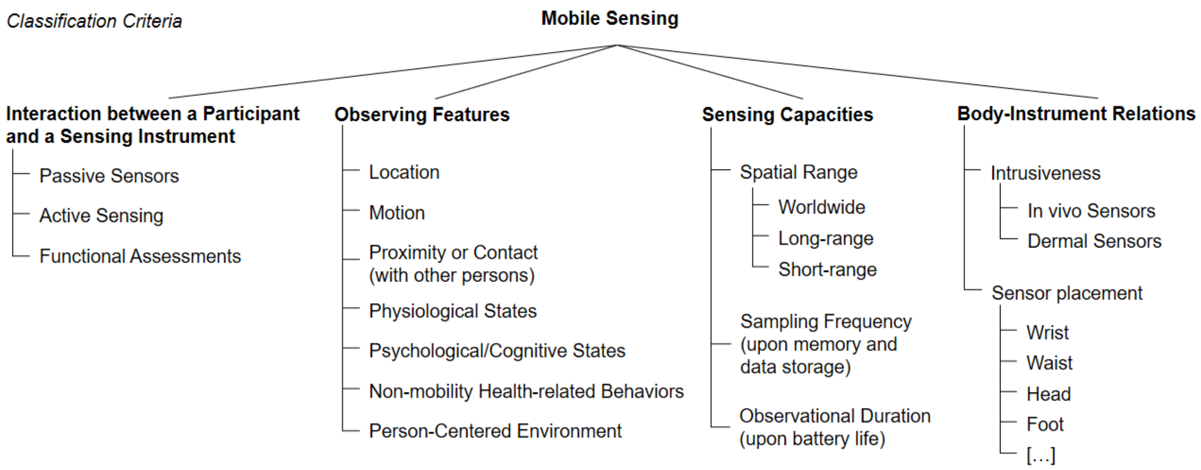

Figure 1. Taxonomy of mobile sensing.

Table 1. Classification of mobile sensing instruments

Interaction between a participant and a sensing instrument	**Observing features**	**Exemplary sensing instrument**
(a) Passive sensors	(i) Location	GPS; Wi-Fi positioning (e.g., indoor positioning – He & Chan, 2016; outdoor positioning – B. Li et al., 2008); Cell tower trilateration; Altimeter; Passive infrared sensor (e.g., Botros et al., 2022)
	(ii) Motion	IMU – Accelerometer; Gyroscope; Magnetometer (e.g., Allahbakhshi et al., 2019, 2020); Pedometer; Kinetic motion sensor; Video (e.g., Osborne & Jones, 2017); Foot pressure sensor; Cycle computer
	(iii) Proximity/contact (with other persons)	Bluetooth (Beacon); Microphone for sound recording (e.g., Mehl, 2017)
	(iv) Physiological states	Heartrate monitor; Pulse oximetry for blood oxygen saturation level; Glucose monitor for blood glucose (e.g., glucose monitor – Rodriguez-León et al., 2021); Electrodermal activity for stress; Breath rate sensor for respiratory rate; Perspiration (e.g., sweat sensors – Bariya et al., 2018)
	(v) Psychological, emotional, and cognitive status	Using physiological sensors – Heartrate monitor; Galvanometer (e.g., Birenboim et al., 2019); Using behavioral sensors – Video camera for face recognition; Eye tracker; Facial motion sensor; Microphone for voice recording.
	(vi) Non-mobility health-related behaviors	Sensors for cigarette smoking (e.g., Imtiaz et al., 2019); Automatic Ingestion Monitor (AIM); Dietary behaviors (e.g., sensing fork – Kadomura et al., 2013)
	(vii) Person-centered environment	Sound – Electronically Activated Recorder (EAR) (e.g., Mehl, 2017); noise (e.g., Ma et al., 2020); Visual – Video recorder; Air quality – Air quality sensor (e.g., GeoAir – Park et al., 2021; Airbeam – Tao, Chai, et al., 2021); Atmospheric condition – Humidity, Thermometer, Ultraviolet, Barometer (e.g,. temperature and humidity – Hass & Ellis, 2019; Schnell et al., 2021);

		<u>Ambient population</u> – Wi-Fi; Cell phone networks; <u>Light</u> – Photodetector
(b) Active sensing	(i ~ vii) any of features	GEMA or EMA (e.g., MOASIS – Röcke et al., 2022; MINDMAP & HANC – Fernandes et al., 2021); Electronic travel/activity diaries (e.g., Fuller et al., 2021; Zhao et al., 2021); Chatbot-enabled interviews (e.g., Flo, a health app for menstruation cycles and pregnancy – Flo, 2022)
(c) Functional assessments	(i) Location; (ii) Motion	Physical ability tests • 6-minute walk test (e.g., Salvi et al., 2020) • a real-life gait measurement (e.g., Giannouli et al., 2022)
	(iv) Physiological states	Medical kit; Body temperature; Blood pressure; Blood glucose; Infectious disease self-diagnostic kit
	(v) Psychological, emotional, and cognitive status	Cognitive ability tests • mobile-app-based memory test (e.g., Röcke et al., 2022) Instructed tasks • voice recording task of reading out loud a sentence (e.g., Fagherazzi et al., 2022)

3. How Mobile Sensing Transforms Research in Sensor-based Mobility, Health, and Place

Mobile sensing has transformed the way mobility and place are considered in health and well-being research in various disciplines. These innovative tools have contributed to observing individualized differences and processes in ill-health and health-related behaviors between places and unveiling intertwined relations between individuals' characteristics and behaviors, changing environments, and their health and well-being in fine-scale space and time (Chaix, 2018).

Key transformations are as follows. First, objective measurements using mobile sensing have been adopted and complemented to self-reports. This has alleviated misclassification of activity and travel behaviors (e.g., physical activity – Hurvitz et al., 2014) and estimation errors in exposure by filling data gaps and cross-checking (Chaix, 2018). Second, frequent or even continuous measurement in real-life settings, without heavy burden on a participant, has become possible and played a key role in reducing spatial, temporal, behavioral, and situational uncertainties with higher spatiotemporal precision. Third, methodological innovations have burgeoned along with technical advances. Moving from survey-only intermittent data collection (e.g., biannual longitudinal survey), *intensive longitudinal methods*—a series of frequently repeated sequential measurements to examine individuals' functional change processes, as opposed to the status quo, that are evolved within each individual over time—have become a norm when using mobile sensing in research and have enabled analyzing within-person changes and processes (Bolger & Laurenceau, 2013; Hoppmann & Riediger, 2009; Mehl & Conner, 2011). Fourth, new multi-channel and multi-sourced sensing data collection and processing methods have given birth to novel *digital biomarkers*, defined as digital physiological and behavioral measures (e.g., step count, sleep duration) that explain and predict health-related outcomes (Sim, 2019), and improved exposure measures. Sixth, integrating data through common attributes of timestamps and geographic coordinates across datasets have generated multi-layered individual behavior and health data and enhanced the understanding of cognitive and decision-making processes and situational/contextual backgrounds that lead to particular types of space-time behaviors and health outcomes (Kestens et al., 2016). Finally, beyond understanding, more personalized and situation-adaptive intervention has become possible with real-time mobile sensing (Nahum-Shani et al., 2018).

4. Challenges in Data

Study design and data collection. Using mobile sensing technologies in research requires careful study design and planning before the data collection phase as well as support to participants during execution of data collection. There are several important components to consider including: (1) target population, (2) participants' tasks, (3) choice and parameterization of mobile sensing instruments, (4) stakeholders, (5) data infrastructure, and (6) technical support, in this procedure:

Target population. Study design needs to consider target population—e.g., by age, sex, region, health status, and education level. Subpopulation groups may have different digital literacy skills and mobile device adoption rates (Sim, 2019). Despite increased acceptance of health-related mobile sensors in older adults (Seifert & Vandelanotte, 2021), a digital divide exists wherein lower-income, disabled, rural populations and older adults are less likely to have a smartphone and Internet access (Sim, 2019), perhaps due to the lack of interest, affordability, or technological literacy. Hence, it is important to consider target population characteristics and provide participants with detailed instructions and extra support for using mobile sensors (e.g., how to operate devices, how to interpret visual signals or displayed contents). Further, sample size and sampling methods via participant recruitment should be adequate to include the representative target subgroups.

Participants' tasks. Participants' tasks are determined by target features to observe and sensing tools. Types and workloads of participants' tasks for passive/active sensing can burden participants and be intrusive to their daily life patterns. Active sensing requires one's self-reports and self-assessments, while passive sensing needs a person to charge and carry sensors. The higher participant burden could lead to a higher drop-off rate, for which we need to consider the tradeoffs between the amount of information to collect and participant burden.

Mobile sensing instruments. Sensor selection involves technical, practical, and user's perspectives. Performance in accuracy, precision, and energy-efficiency may vary by sensors and devices. Sensing performance affects data quality and user's drop-off rate; more accurate activity trackers can retain more users, thanks to better utility (Henriksen et al., 2020). Deploying multiple (high-performance) sensors could benefit data quality and validation because of the complementary capabilities of different sensing approaches (e.g., capability comparison of research methods – Table 2 in Miller, 2012), but it could be costly and inaccessible for many researchers (Chaix, 2018). For users, sensor devices should be usable and acceptable through ease-of-use and comfort design (e.g., size, weight, interface) and functionalities (e.g., privacy protection). Usability and acceptability can be measured by willingness to use and keep, simplicity, reliability, wearable time, satisfaction, and activity interference (Baig et al., 2019; Klaassen et al., 2016). It is necessary to conduct preliminary assessments and get participants' feedback on sensor performance and usability before implementing large-scale experiments (e.g., fitness tracker comparison – Tedesco et al., 2019).

Stakeholders. Health-related studies involve diverse stakeholders (e.g., research collaborators, medical practitioners). To make broader impacts through comparative studies, using compatible study protocols or frameworks would be critical (e.g., a review on frameworks – Kumar et al., 2021). To integrate with clinical care, it is important to engage medical practitioners in the study (e.g., Giannouli et al., 2022) and develop digital biomarkers directly associated with clinical outcomes (Sim, 2019). Applying data interoperability standards (e.g., Fast Healthcare Interoperability Resources (FHIR) – ONC, 2022) is essential to integrate existing electronic health record systems (Sim, 2019).

Data infrastructure. Study design and data collection further entail pragmatic plans for data transfer, data curation, and compatibility. Some studies request participants to revisit a lab to transfer data to the data storage while others send data to the data server in real time. Sensor data could be large and need large databases to store them (e.g., video, IMU). For heterogeneous sensing data, it is useful to build linked data possibly using knowledge graphs that can help extract knowledge from semantic networks constructed across different datasets (e.g., health-related IoT – Mastropietro et al., 2021; geospatial human activities – Dashdorj et al., 2018).

Technical support. Sensor-based measurements require careful planning of trouble-shooting process pipelines and an infrastructure ready to respond to technical problems that may arise during data collection (e.g., telephone support to ensure imminent trouble shooting or maintenance of participant motivation) and curation.

Data quality and (pre)processing. Despite careful study design and data collection, recent mobile sensing technologies and complexity of human behaviors accompany many challenges in constructing high-quality individual behavior and health data. Data quality can vary with sensor quality and participant’s behaviors, so researchers are tasked with assessing data quality and improving it through data (pre)processing.

Measurement errors. Errors in measurement yield low-quality data. Measurement errors can originate from various sources: participant’s mistakes, systematic errors, or random errors (Yan et al., 2013). First, participants can make mistakes even after comprehensive instructions (e.g., forgetting to charge/carry devices, breaking or missing devices, missing self-report notifications, reporting misinformation). This can result in data gaps and biases. Second, systematic errors are due to limitations of sensing instruments and/or environments. Specifically, GPS has more signal losses indoors or in urban canyons, and physiological sensors appear less accurate when moving; thus, contextual information should be combined to detect and address systematic errors (Birenboim et al., 2019). Preventive approaches for such systematic errors could be considered in the study design phase. Third, random errors refer to unpredictable errors that shift a measurement from its true value by a random amount (e.g., GPS signal noise).

Data preprocessing and integration. Systematic and random measurement errors can partially be resolved by (automated) data preprocessing, cleaning, and integration but potentially propagated in data processing and analysis. Noise removal and interpolation techniques can alleviate the impact of signal noise (e.g., Butterworth, moving average, median, low-pass, high-pass, or non-linear filters; Allahbakhshi et al., 2019; Incel et al., 2013). Imputation methods for data gaps or missing data points can potentially prevent error propagation (e.g., GPS data imputation – Yoo et al., 2020). Integrated heterogeneous datasets through multi-sensor fusion or linked databases may contribute to filling data gaps of one another. As an example, data integration of indoor and outdoor location sensing enables locations between indoors, garden at home, and close neighborhood to be distinguished, which yields a more accurate ‘time out of home’ measure. Multi-sensor fusion leads to better activity recognition performance; for instance, GPS/IMU sensor fusion improved real-life physical activity type detection (Allahbakhshi et al., 2020). Similarly, momentary self-reports are complementary to activity sensor data for activity inference and validation. In data integration, a timestamp is the most important meta-variable to link all observed features together (Chaix, 2018); time synchronization across all sensors is critical and can be achieved by using the same time system (e.g., initiating all devices on the same computer with a world atomic clock – Sila-Nowicka & Thakuriah, 2019). Geographic coordinates are also fundamental to link person-centered measurement to context features including environmental features.

Semantically enriched trajectory construction. Multi-channel high-resolution mobile sensing creates an opportunity to observe a full picture of momentary individual behaviors and social/environmental interactions, and is challenging (Martin et al., 2018). Based on such rich data, behavioral and situational patterns can be annotated to daily movement trajectories through semantic trajectory enrichment techniques, which includes stop-move detection (e.g., Bermingham & Lee, 2018; Hwang et al., 2018; Montoliu et al., 2013; Thierry et al., 2013), transport mode detection (e.g., Berjisian & Bigazzi, 2022; Huang et al., 2019; Roy et al., 2022), trip purpose inference (e.g., Nguyen et al., 2020), physical activity recognition (e.g., Allahbakhshi et al., 2019), and indoor activity detection (e.g., Botros et al., 2022) from raw sensor-based data and linking back to mobility patterns (Yan et al., 2013). In this process, contextual data (e.g., POI data, land use data) overlaid with sensor data help infer activities and situations (Psyllidis et al., 2022). Geo-located social media data are another source to enrich individuals’ activity space (e.g., Hu et al., 2020; Lee et al., 2016).

5. Challenges in Analysis

Measuring and characterizing mobility patterns. Mobility pattern measurements have become more sophisticated, ranging from sensorless approaches (e.g., interactive map-based questionnaires) to sensor-based mobility tracking. One of the key challenges in modelling mobility patterns lies in representing their multidimensional nature (Fillekes et al., 2019; Hasanzadeh, 2019; Perchoux et al., 2014). Individual-level activity spaces are commonly represented by spatial metrics including daily path area and buffer area centered on visited locations (L. Smith et al., 2019). Such geometry-based spatial measures only make partial use of rich information that mobile sensing captures (Fuller & Stanley, 2019). Instead, human mobility is multidimensional and represented in various forms (e.g., six latent dimensions of daily mobility – Fillekes et al., 2019). Mobility indicators represent not only space (e.g., count of locations, extent, shape) but also time (e.g., duration, timing, temporal distribution), movement scope (e.g., stop, move, trajectories), and their attributes (e.g., transportation modes, trip destinations). (Bayat et al., 2021; Fillekes et al., 2019). Such more comprehensive modeling of mobility patterns thus translates into more accurate assessment of exposures and health relationships. For instance, the entropy of visited places characterizes time-use distribution over visited places and can serve as a proxy of the diversity of exposure to different places (Fillekes et al., 2019). Borrowing concepts and methods from other disciplines is a good practice to expand the set of mobility indicators. The concepts of space-time fragmentation of activities in time geography (e.g., Hubers et al., 2018; Lizana et al., 2022), fractal dimension (e.g., Zhang et al., 2018), and distance-based burstiness for trajectory data (e.g., Kim & MacEachren, 2014) from complexity science have been used to measure the complexity of mobility patterns. Group behaviors in mobility can be characterized as co-location and synchronized trajectory patterns through trajectory similarity measures (e.g., Tao, Both, et al., 2021) and spatiotemporal metrics for dyadic relationships (e.g., Timmons et al., 2017).

Spatial, temporal, behavioral, and situational uncertainties in exposure measurement. Defining the true and causally relevant geographic context for environmental exposure is challenging. Uncertainties in measuring personal exposures arise from how we observe and model one's behaviors and (in)direct interactions with their contexts that are associated with actual/potential health and well-being outcomes. One of the well-known concepts is the Uncertain Geographic Context Problem (UGCoP); a misspecification of the geographic context—linked to uncertainties in spatial and/or temporal modeling of individual mobility patterns—introduces biases in exposure variables and estimation of contextual effects (Kwan, 2012). Uncertainties can be viewed from the perspective of spatiotemporal representation and quantification of effective exposure and its related factors (i.e., *spatial/temporal uncertainties*). Uncertainties may also relate to underlying behavioral/situational conditions and processes that affect the exposure level and its impact but are not simply substituted by spatiotemporal quantities (e.g., area, duration) (i.e., *behavioral/situational uncertainties*). Mobile sensing approaches have advanced exposure estimation of individuals by reducing spatial, temporal, behavioral, as well as situational uncertainties with multidimensional and fine-scale observations, although new technologies come with new measurement uncertainties as discussed in Section 4.

Spatial uncertainty. Exposure measures and their impacts can vary across different environments—captured in an environmental layer as points, lines, areas, and surfaces—and mobility representations (e.g., all GPS points, stop locations). Numerous studies compared different shapes, scales, and foci of spatial contexts for exposure measures (e.g., residential, non-residential, and travelled environments) or activity space representations (e.g., buffers around visited locations, buffered daily path, kernel density estimates). Their results exhibited strong discordances in exposure estimates over different spatial configurations (Hurvitz et al., 2014; J. Kim & Kwan, 2021; Perchoux et al., 2016; Wray et al., 2021). Modeling personal exposure in spatial dimensions should notably consider spatial interactions by which an environmental attribute influences a certain behavior or outcome. For instance, if the environment mostly exerts its influence via a sensory experience (e.g., food stressors on smells, sounds of people eating in restaurants), 21-50 m buffers along the GPS tracks is recommended to mimic visual or olfactory interaction with the environment (e.g., Scully et al., 2019) (Chaix, 2018). In contrast, larger accessibility and visibility measures (e.g., 100-200 m buffer for accessibility) reflect the ability of individuals to explore their surroundings to access or benefit from an urban resource (Chaix, 2018). Some exposure measures encompass both experienced and non-experienced areas—e.g., relatively large buffers of 1-2 km around visited locations—to reflect potentially influential environmental attributes (e.g., air pollution emitted by neighboring industries), or potential individual accessibility to visit a location upon their knowledge of surroundings.

Temporal uncertainty. The temporal dimension, a factor of processes underlying exposure, has been integrated in exposure measurement (Kwan, 2018). When time integration was in its infancy, two oversimplified approaches emerged and are still adopted in practice: (1) averaging and (2) contemporaneous momentary approaches. First, the averaging approach attributes the same weight to an environmental exposure in one's visited space, without respect to temporal attributes of mobility behaviors (e.g., duration of stay in a place). Such practice leads to underestimated exposure in longer-visited places. Alternatively, time-weighted spatial averaging (TWSA) methods have been adopted (Poom et al., 2021); TWSA produces exposure estimates weighted by the expected or actual time spent at each location (e.g., Li et al., 2018; Perchoux et al., 2015, 2016) and each travel path (e.g., Jankowska et al., 2015; Scully et al., 2019; Wang et al., 2018). In this special issue, Jankowska et al. (2021) compared the reliability of three TWSA approaches to GPS-based environmental exposure, which informs methodological choice. In search for a dose-response relationship, duration of exposure may approximate accumulated exposure that can onset health impacts when exceeding the minimum threshold (Jankowska et al., 2021). Thus, the minimum threshold in duration of exposure needs to be considered in relating to health outcomes. Second, the contemporaneous momentary approach attributes the effect of a momentary exposure to a momentary outcome based on point-by-point information, independently of continuous and long-term changes and prior conditions of one's status, behaviors, situations, and exposures (Chaix et al., 2013). Factors seemingly associated with exposure at a moment may yield insignificant exposure and only marginal health impacts. Some studies attempted to leverage diverse analytical methods to reveal temporal dynamics of phenomena. For instance, a sequence or timing of exposure can be critical to shaping health behaviors—e.g., the effect of sequential and space-time patterns of activities and grocery retailer exposure on food-related behaviors (Liu et al., 2021).

Behavioral and situational uncertainties. Behavioral and situational aspects in personal exposure are not always intuitively represented as spatiotemporal quantities and often construct semantic attributes of mobility patterns. Some biases in exposure estimation intrinsically originate from the complex dynamics of human behaviors and constantly changing situations. Mobile sensing and accompanied analytical techniques have been the key solution to tackle the behavioral/situational uncertainties in exposure, as discussed about benefits of multi-sensor mobile sensing in Section 4. Some studies addressed this type of uncertainties by distinguishing exposure in different mobility behaviors (e.g., stationary time, walking time, and in-vehicle time – Jankowska et al., 2021). As another example, a smoking behavior detection sensor can help distinguish respiratory disease risk mainly contributed by smoking from the risk increased by exposure to air pollution, which can inform us where to put smaller weights of air pollution exposure. Exposure to social interactions can be inferred based on trip destination characteristics (e.g., activity type, sociability) via linking GPS to POI data and trip purpose inference as well as human voice detection via audio sensing and momentary self-reports on accompanied persons.

6. Challenges in Interpretation and Practices

Although we can resolve uncertainties in measurement and analysis by integrating rich and fine-grained sensing data and developing appropriate spatiotemporal representations, this does not guarantee flawless interpretations of statistical inferences for causal relationships between mobility behaviors, environment, and health, owing to potential biases. One of the well-known biases in interpreting causal relations is *ecological fallacy* bias—a group's characteristics are not the same as its members' traits, and human behaviors and environmental impacts appear rather stratified by sub-population groups (e.g., stratified effects of COVID-19 on outdoor walking by sociodemographic factors – Hunter et al., 2021). Likewise, there are several biases that can arise in interpretation. Here, we discuss noteworthy biases and suggest ways to handle them in research.

Residential effect fallacy bias. Classical residential neighborhood and health studies are subject to the *residential effect fallacy* bias (Chaix et al., 2017). The residential effect fallacy indicates overestimation of the true residential neighborhood effect and stems from drawing a conclusion on associations between residential-based exposure measures and health outcomes without regard to potential contributions of non-residential exposures, when exposure levels in each of residential and non-residential neighborhoods have similarities (Chaix et al., 2017)—e.g., little variations in air pollution concentrations across residential and non-residential neighborhoods. The residential neighborhood effect may be significant for some population segments more bounded within their local neighborhood, including older adults with sedentary lifestyles (Van Cauwenberg et al., 2018). However, even in less mobile subgroups, heterogeneity in mobility patterns and exposure to their residential neighborhood may vary. Less frequent visits to non-residential areas can be intense and have impacts on health and well-being—e.g., the effect of infrequent long-distance trips on life satisfaction (Luo et al., 2022).

Selective daily mobility bias. Self-selection processes lead individuals to visit particular places, based on their own preferences and values beyond essential needs, to pursue a behavior of interest and this makes it difficult to infer causal relationships between environments, behaviors, and health (Chaix et al., 2012, 2013, 2016). Neglecting such decision-making processes can introduce *selective daily mobility bias*—an overestimation of the effect of environmental and situational conditions (e.g., accessibility to greenspaces) on mobility and behaviors (e.g., sport practices – Shrestha et al., 2019). In this special issue, Klein et al. (2021) have observed that its magnitude may further vary by behaviors, and notably by transport mode. So far, very few studies have empirically tackled this bias (e.g., Burgoine et al., 2015; Plue et al., 2020; Shrestha et al., 2019) yet a clear-cut conclusion on the magnitude of this bias has not been drawn because of the diverse methodological approaches, and various and often diverging outcomes.

Embracing selective daily mobility imposes another challenge in causal inference. Researchers essentially have to distinguish the preference effect on behaviors from other effects (e.g., accessibility, amenity). One of the solutions is to filter GPS tracks to define one's truncated activity space, based on visited places/paths that do not result heavily from own preferences (e.g., Howell et al., 2017; Klein et al., 2021; Scully et al., 2019; Shrestha et al., 2019). Integrating sensors with momentary or daily-basis self-reports and functional assessments will be one strategy to obtain information on underlying decision-making processes, activity engagement, and preconditions (Klein et al., 2021; Plue et al., 2020).

Group behavior bias. Some living resources (e.g., food, car) and activities (e.g., family picnic, sports) are shared at a group level (e.g., household, friends). *Group behavior bias* occurs when only considering individual-level behaviors and environments and ignoring (1) resources shared to the entire group but accessible or obtained by only a part of group members (Corfman & Gupta, 1993), or (2) limited shared resources for which each member of a group needs to compete or cooperate, as well as (3) group activities based on shared decision-making processes and interest.

First, regarding shared resources, personal exposure to the resources can be different for each member of a group who has their own activity spaces, but the exposure can be moderated by activity spaces of other household members. A caveat exists against assuming equal consumption of the collective resources because each member will consume these based on their preferences, habits, and restrictions. Smith et al. (2022)'s study is a good example of how group behavior bias can be integrated in food exposure and mobility research; they compared access to food retailers as an exposure measure at individual and household levels and found within-household differences in access to food, moderated by neighborhood factors. Second, for limited resources, group members are in a competing or cooperating relationship. For instance, when one household member uses a household-shared car, another member's potential activity space will shrink. When members carpool while making synchronized mobility patterns, one may experience unintended detours and exposure. Third, activities shared by the group are determined by joint decision and socialization processes, and may expose individuals to similar external stimuli. Group members may have different roles in the group (e.g., leader, follower). Their preferences and constraints may not be equally reflected in decision-making processes. Health impacts of shared experiences will be individualized based on personal conditions. Hence, causes and effects of group behaviors need to be disentangled from those of individual behaviors.

Ergodicity bias: a reason for scrutinizing within-person differences. There are several theories supporting that statistical inferences from a group are not necessarily generalizable to its individuals. Similar to ecological fallacy mentioned above and *Simpson's paradox* that describes the disassociation between subgroups' trends and the aggregate trend of the entire group, *ergodicity* or *nonergodicity* is a mathematical concept framing the generalizability of statistical phenomena throughout different levels and units (e.g., within-person vs. between-person levels; individuals vs. subgroups vs. whole group) (Fisher et al., 2018). *Ergodicity bias* occurs when taking ergodicity for granted for human behaviors and health statuses/outcomes that are inherently nonergodic due to biological structure (e.g., development, growth, aging) and social processes (e.g., learning) (Mangalam & Kelty-Stephen, 2021; Molenaar, 2004). If the phenomenon is ergodic, applying only cross-sectional approaches and eliminating time dimension is justified, because ergodicity conditions require both homogeneity and stationarity of statistical processes across different levels and units (Fisher et al., 2018; Mangalam & Kelty-Stephen, 2021).

To avoid this bias, several research methods have been proposed and practiced, including intensive longitudinal approaches, multilevel modeling approaches, and statistical tests for ergodicity. First, many sensing-derived studies on individuals have deployed intensive longitudinal methods in study design and analysis. Second, multilevel modeling approaches have been devised to address complex multilevel dependencies between data points; multilevel modeling allows distinguishing within-person and between-person sources of variation (e.g., Ram & Gerstorf, 2009). Third, statistical testing for ergodicity has been suggested. It is recommended to examine the consistency of mean and standard deviation for distribution comparisons as well as the consistency of bivariate and multivariate covariation among variables for statistical inferences on variable relations, across groups and individuals (Fisher et al., 2018).

Sensing to intervene. Behavioral interventions using mHealth technology (see Appendix A) have the potential to positively impact health. Portable devices can be used to motivate an individual toward healthy behavior, such as increasing physical activity or supporting situational awareness in health-constraining places (e.g., alcohol outlets) (Hardeman et al., 2019). Just-in-time adaptive interventions (JITAIs) are particularly aimed at supporting positive health behaviors in real time, based on situational risk and opportunities, and are therefore tailored to environmental and behavioral contexts and prompted by mobile devices (Hardeman et al., 2019; Nahum-Shani et al., 2018). JITAIs rely on actively engaging through prompts and/or passive sensing of user states and behaviors (Nahum-Shani et al., 2018). In addition to sensing-related challenges, JITAIs are challenged with finding consistency in study design and consensus among research endeavors, because they are dynamically tailored to individual activities and situations. There remain knowledge gaps around to what extent JITAIs are effective in changing behavior, especially outside of clinical settings, partly because conventional study design and modeling approaches are often inappropriate for assessing variation in situational factors inherent to intervention design (Golbus et al., 2021; Nahum-Shani et al., 2018).

Visualizing mobility and health data for stakeholders. While visualization is a useful tool to intuitively explore and communicate data, large volumes of individual mobility data are visually overwhelming and translating data to displays is challenging—e.g., privacy concerns are at the forefront of displaying mobility and health data. Interactive dashboards are one way to distill mobility and health data into information that aids exploring multidimensional relations and making decisions (e.g., COVID-19 – Gao et al., 2020). Dashboards are flexible enough to enable information and knowledge discovery for end-users with various levels of experience and domain knowledge. Clear and user-friendly displays improve research impacts by making outputs accessible to various stakeholders for real-world impacts. Potential users include individuals that make decisions or participate in health or behavioral interventions based on their sensed and visualized self (e.g., Choe et al., 2017), health practitioners that monitor patients for tailored treatments and inventions, and governments and councils that may gain insights for making data-driven decisions in planning and policy related to mobility and environments.

7. Conclusion

Although the last two decades have witnessed major progress in the development of sensor-based research in public health, geography, social sciences, and medical sciences, major challenges remain to be addressed that pertain to data collection, processing, analysis, interpretation, and practices. Scholars in this special issue all contribute in their own way by advancing data collection through sensor/device comparison and data representativeness/quality validation (Fuller et al., 2021; Zhao et al., 2021), comparing exposure estimation approaches while considering spatial, temporal, and behavioral uncertainties (Jankowska et al., 2021; Wray et al., 2021), disentangling selective mobility bias associated with travel path and modal choices (Klein et al., 2021), and conducting a collective mobility and health study with large-scale individual mobility data (Long et al., 2021), paving the way to advance sensor-based research at the intersection of *Mobility, Health, and Place* and tackle remaining and upcoming challenges.

Nomenclature

Abbreviation	Explanation
ADL	Activity of Daily Life
AIM	Automatic Ingestion Monitor
BT	Bluetooth
COVID-19	Coronavirus Disease 2019; the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2)
EAR	Electronically Activated Recorder
EMA	Ecological Momentary Assessment
FHIR	Fast Healthcare Interoperability Resources
GEMA	Geographic Ecological Momentary Assessment
GPS	Global Positioning System
IMU	Inertial Measurement Unit
IoT	Internet of Things
JITAI	Just-In-Time Adaptive Intervention
POI	Point of Interest
TWSA	Time-Weighted Spatial Averaging
UGCoP	Uncertain Geographic Context Problem
U.S.	The United States
Wi-Fi	Wireless Fidelity

Appendix A

Table A1. Relevant concepts in mobile sensing and health.

Concept	Description
Mobile sensing in public health (Chaix, 2018)	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. Sensor-based studies in the field of public health assess environmental exposures using either GPS data or a dedicated device; of particular interest were studies that combined several tools.
Mobile health (Sim, 2019)	The application of sensors, mobile apps, social media, and location-tracking technology to obtain data pertinent to wellness and disease diagnosis, prevention, and management – makes it theoretically possible to monitor and intervene whenever and wherever acute and chronic medical conditions occur.
mHealth (WHO, 2011)	Medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants, and other wireless devices. mHealth involves the use and capitalization on a mobile phone's core utility of voice and short messaging service as well as more complex functionalities.
Portable sensing in urban mobility (Birenboim et al., 2021)	Portable sensing includes any information that can be gauged about the status of an event or a stimulus through an electronic device. This includes smart cards that embed radio-frequency identification (RFID) technology, as well as people who report their affective status or their immediate environment through their smartphones using repeat frequent surveys (also known as ecological momentary assessment).
Portable sensors (Birenboim et al., 2021)	Lightweight devices that can respond to physical stimuli or events and log or transmit their readings to other electronic devices. Portable sensors are usually compact, have low power consumption, and are capable of wireless communication with other devices.
Ecological Momentary Assessment (EMA) (Shiffman et al., 2008)	Methods using repeated collection of real-time data on subjects' behavior and experience in their natural environments.

References

Allahbakhshi, H., Conrow, L., Naimi, B., & Weibel, R. (2020). Using Accelerometer and GPS Data for Real-Life Physical Activity Type Detection. *Sensors*, *20*(3), 588. https://doi.org/10.3390/s20030588

Allahbakhshi, H., Hinrichs, T., Huang, H., & Weibel, R. (2019). The key factors in physical activity type detection using real-life data: A systematic review. *Frontiers in Physiology*, *10*(FEB), 1–20. https://doi.org/10.3389/fphys.2019.00075

Baig, M. M., Afifi, S., GholamHosseini, H., & Mirza, F. (2019). A Systematic Review of Wearable Sensors and IoT-Based Monitoring Applications for Older Adults – a Focus on Ageing Population and Independent Living. *Journal of Medical Systems*, *43*(8), 233. https://doi.org/10.1007/s10916-019-1365-7

Bariya, M., Nyein, H. Y. Y., & Javey, A. (2018). Wearable sweat sensors. *Nature Electronics*, *1*(3), 160–171. https://doi.org/10.1038/s41928-018-0043-y

Bayat, S., Naglie, G., Rapoport, M. J., Stasiulis, E., Widener, M. J., & Mihailidis, A. (2021). A GPS-Based Framework for Understanding Outdoor Mobility Patterns of Older Adults with Dementia: An Exploratory Study. *Gerontology*, 1–15. https://doi.org/10.1159/000515391

Berjisian, E., & Bigazzi, A. (2022). Evaluation of methods to distinguish trips from activities in walking and cycling GPS data. *Transportation Research Part C: Emerging Technologies*, *137*(December 2021), 103588. https://doi.org/10.1016/j.trc.2022.103588

Bermingham, L., & Lee, I. (2018). A probabilistic stop and move classifier for noisy GPS trajectories. *Data Mining and Knowledge Discovery*, *32*(6), 1634–1662. https://doi.org/10.1007/s10618-018-0568-8

Birenboim, A., Dijst, M., Scheepers, F. E., Poelman, M. P., & Helbich, M. (2019). Wearables and Location Tracking Technologies for Mental-State Sensing in Outdoor Environments. *Professional Geographer*, *71*(3), 449–461. https://doi.org/10.1080/00330124.2018.1547978

Birenboim, A., Helbich, M., & Kwan, M. P. (2021). Advances in portable sensing for urban environments: Understanding cities from a mobility perspective. *Computers, Environment and Urban Systems*, *88*(April), 101650. https://doi.org/10.1016/j.compenvurbsys.2021.101650

Bolger, N., & Laurenceau, J.-P. (2013). *Intensive Longitudinal Methods: An Introduction to Diary and Experience Sampling Research*. Guilford Press.

Botros, A. A., Schuetz, N., Röcke, C., Weibel, R., Martin, M., Müri, R. M., & Nef, T. (2022a). Eigenbehaviour as an Indicator of Cognitive Abilities. *Sensors*, *22*(7), 2769. https://doi.org/10.3390/s22072769

Botros, A. A., Schuetz, N., Röcke, C., Weibel, R., Martin, M., Müri, R. M., & Nef, T. (2022b). Eigenbehaviour as an Indicator of Cognitive Abilities. *Sensors*, *22*(7), 2769. https://doi.org/10.3390/s22072769

Burgoine, T., Jones, A. P., Namenek Brouwer, R. J., & Benjamin Neelon, S. E. (2015). Associations between BMI and home, school and route environmental exposures estimated using GPS and GIS: do we see evidence of selective daily mobility bias in children? *International Journal of Health Geographics*, *14*(1), 8. https://doi.org/10.1186/1476-072X-14-8

Chaix, B. (2018). Mobile Sensing in Environmental Health and Neighborhood Research. *Annual Review of Public Health*, *39*, 367–384. https://doi.org/10.1146/annurev-publhealth-040617-013731

Chaix, B., Duncan, D., Vallée, J., Vernez-Moudon, A., Benmarhnia, T., & Kestens, Y. (2017). The "Residential" effect fallacy in neighborhood and health studies: Formal definition, empirical identification, and correction. *Epidemiology*, *28*(6), 789–797. https://doi.org/10.1097/EDE.0000000000000726

Chaix, B., Kestens, Y., Duncan, D. T., Brondeel, R., Méline, J., El Aarbaoui, T., Pannier, B., & Merlo, J. (2016). A GPS-Based Methodology to Analyze Environment-Health Associations at the Trip Level: Case-Crossover Analyses of Built Environments and Walking. *American Journal of Epidemiology*, *184*(8), 579–589. https://doi.org/10.1093/aje/kww071

Chaix, B., Kestens, Y., Perchoux, C., Karusisi, N., Merlo, J., & Labadi, K. (2012). An interactive mapping tool to assess individual mobility patterns in neighborhood studies. *American Journal of Preventive Medicine*, *43*(4), 440–450. https://doi.org/10.1016/j.amepre.2012.06.026

Chaix, B., Méline, J., Duncan, S., Merrien, C., Karusisi, N., Perchoux, C., Lewin, A., Labadi, K., & Kestens, Y. (2013). GPS tracking in neighborhood and health studies: A step forward for environmental exposure assessment, a step backward for causal inference? *Health & Place*, *21*, 46–51. https://doi.org/10.1016/j.healthplace.2013.01.003

Choe, E. K., Lee, B., Zhu, H., Riche, N. H., & Baur, D. (2017). Understanding self-reflection: How people reflect on personal data through visual data exploration. *PervasiveHealth: Pervasive Computing Technologies for Healthcare*, 173–182. https://doi.org/10.1145/3154862.3154881

Corfman, K. P., & Gupta, S. (1993). Chapter 3 Mathematical models of group choice and negotiations. In *Handbooks in Operations Research and Management Science* (Vol. 5, Issue C, pp. 83–142). https://doi.org/10.1016/S0927-0507(05)80026-X

Dashdorj, Z., Sobolevsky, S., Lee, S., & Ratti, C. (2018). Deriving human activity from geo-located data by ontological and statistical reasoning. *Knowledge-Based Systems*, *143*, 225–235. https://doi.org/10.1016/j.knosys.2017.11.038

Fagherazzi, G., Zhang, L., Elbéji, A., Higa, E., Despotovic, V., Ollert, M., Aguayo, G. A., Nazarov, P. V, & Fischer, A. (2022). A voice-based biomarker for monitoring symptom resolution in adults with COVID-19: Findings from the prospective Predi-COVID cohort study. *PLOS Digital Health*, *1*(10), e0000112. https://doi.org/10.1371/journal.pdig.0000112

Fernandes, A., Van Lenthe, F. J., Vallée, J., Sueur, C., & Chaix, B. (2021). Linking physical and social environments with mental health in old age: a multisensor approach for continuous real-life ecological and emotional assessment. *Journal of Epidemiology and Community Health*, *75*(5), 477–483. https://doi.org/10.1136/jech-2020-214274

Fillekes, M. P., Giannouli, E., Kim, E.-K., Zijlstra, W., & Weibel, R. (2019). Towards a comprehensive set of GPS-based indicators reflecting the multidimensional nature of daily mobility for applications in health and aging research. *International Journal of Health Geographics*, *18*(1), 17. https://doi.org/10.1186/s12942-019-0181-0

Fisher, A. J., Medaglia, J. D., & Jeronimus, B. F. (2018). Lack of group-to-individual generalizability is a threat to human subjects research. *Proceedings of the National Academy of Sciences*, *115*(27), E6106–E6115. https://doi.org/10.1073/pnas.1711978115

Flo. (2022). *Flo: female health app*. https://flo.health/

Fuller, D., Bell, S., Firth, C. L., Muhajarine, N., Nelson, T., Stanley, K., Sones, M., Smith, J., Thierry, B., Laberee, K., Stephens, Z. P., Phillips, K., Kestens, Y., & Winters, M. (2021). Wave 1 results of the INTerventions, Research, and Action in Cities Team (INTERACT) cohort study: Examining spatio-temporal measures for urban environments and health. *Health & Place*, *June*, 102646. https://doi.org/10.1016/j.healthplace.2021.102646

Fuller, D., & Stanley, K. G. (2019). The future of activity space and health research. *Health & Place*, *58*(July), 102131. https://doi.org/10.1016/j.healthplace.2019.05.009

Gao, S., Rao, J., Kang, Y., Liang, Y., & Kruse, J. (2020). Mapping County-Level Mobility Pattern Changes in the United States in Response to COVID-19. *SSRN Electronic Journal*, 16–26.

https://doi.org/10.2139/ssrn.3570145

Giannouli, E., Kim, E.-K., Fu, C., Weibel, R., Sofios, A., Infanger, D., Portegijs, E., Rantanen, T., Huang, H., Schmidt-Trucksäss, A., Zeller, A., Rössler, R., & Hinrichs, T. (2022). Psychometric properties of the MOBITEC-GP mobile application for real-life mobility assessment in older adults. *Geriatric Nursing*, *48*, 273–279. https://doi.org/10.1016/j.gerinurse.2022.10.017

Golbus, J. R., Dempsey, W., Jackson, E. A., Nallamothu, B. K., & Klasnja, P. (2021). Microrandomized Trial Design for Evaluating Just-in-Time Adaptive Interventions Through Mobile Health Technologies for Cardiovascular Disease. *Circulation: Cardiovascular Quality and Outcomes*, *14*(2), E006760. https://doi.org/10.1161/CIRCOUTCOMES.120.006760

Hardeman, W., Houghton, J., Lane, K., Jones, A., & Naughton, F. (2019). A systematic review of just-in-time adaptive interventions (JITAIs) to promote physical activity. *International Journal of Behavioral Nutrition and Physical Activity*, *16*(1), 31. https://doi.org/10.1186/s12966-019-0792-7

Hasanzadeh, K. (2019). Exploring centricity of activity spaces: From measurement to the identification of personal and environmental factors. *Travel Behaviour and Society*, *14*(October 2018), 57–65. https://doi.org/10.1016/j.tbs.2018.10.001

Hass, A. L., & Ellis, K. N. (2019). Using wearable sensors to assess how a heatwave affects individual heat exposure, perceptions, and adaption methods. *International Journal of Biometeorology*, *63*(12), 1585–1595. https://doi.org/10.1007/s00484-019-01770-6

He, S., & Chan, S.-H. G. (2016). Wi-Fi Fingerprint-Based Indoor Positioning: Recent Advances and Comparisons. *IEEE Communications Surveys & Tutorials*, *18*(1), 466–490. https://doi.org/10.1109/COMST.2015.2464084

Henriksen, A., Sand, A.-S., Deraas, T., Grimsgaard, S., Hartvigsen, G., & Hopstock, L. (2020). Succeeding with prolonged usage of consumer-based activity trackers in clinical studies: a mixed methods approach. *BMC Public Health*, *20*(1), 1300. https://doi.org/10.1186/s12889-020-09406-w

Hoppmann, C. A., & Riediger, & M. (2009). Ambulatory Assessment in Lifespan Psychology An Overview of Current Status and New Trends. *Ambulatory Assessment in Lifespan Psychology European Psychologist*, *14*(2), 98–108. https://doi.org/10.1027/1016-9040.14.2.98

Howell, N. A., Farber, S., Widener, M. J., & Booth, G. L. (2017). Residential or activity space walkability: What drives transportation physical activity? *Journal of Transport & Health*, *7*(September), 160–171. https://doi.org/10.1016/j.jth.2017.08.011

Hu, L., Li, Z., & Ye, X. (2020). Delineating and modeling activity space using geotagged social media data. *Cartography and Geographic Information Science*, *47*(3), 277–288. https://doi.org/10.1080/15230406.2019.1705187

Huang, H., Cheng, Y., & Weibel, R. (2019). Transport mode detection based on mobile phone network data: A systematic review. *Transportation Research Part C: Emerging Technologies*, *101*(September 2018), 297–312. https://doi.org/10.1016/j.trc.2019.02.008

Hubers, C., Dijst, M., & Schwanen, T. (2018). The fragmented worker? ICTs, coping strategies and gender differences in the temporal and spatial fragmentation of paid labour. *Time & Society*, *27*(1), 92–130. https://doi.org/10.1177/0961463X15609830

Hunter, R. F., Garcia, L., de Sa, T. H., Zapata-Diomedi, B., Millett, C., Woodcock, J., Pentland, A. 'Sandy', & Moro, E. (2021). Effect of COVID-19 response policies on walking behavior in US cities. *Nature Communications*, *12*(1), 3652. https://doi.org/10.1038/s41467-021-23937-9

Hurvitz, P. M., Moudon, A. V., Kang, B., Saelens, B. E., & Duncan, G. E. (2014). Emerging Technologies for Assessing Physical Activity Behaviors in Space and Time. *Frontiers in Public Health*, *2*(JAN), 1–15. https://doi.org/10.3389/fpubh.2014.00002

Hwang, S., VanDeMark, C., Dhatt, N., Yalla, S. V., & Crews, R. T. (2018). Segmenting human trajectory data by movement states while addressing signal loss and signal noise. *International Journal of Geographical Information Science*, *32*(7), 1391–1412. https://doi.org/10.1080/13658816.2018.1423685

Imtiaz, M. H., Ramos-Garcia, R. I., Wattal, S., Tiffany, S., & Sazonov, E. (2019). Wearable Sensors for Monitoring of Cigarette Smoking in Free-Living: A Systematic Review. *Sensors*, *19*(21), 4678. https://doi.org/10.3390/s19214678

Incel, O. D., Kose, M., & Ersoy, C. (2013). A Review and Taxonomy of Activity Recognition on Mobile Phones. *BioNanoScience*, *3*(2), 145–171. https://doi.org/10.1007/s12668-013-0088-3

Jankowska, M. M., Schipperijn, J., & Kerr, J. (2015). A Framework for Using GPS Data in Physical Activity and Sedentary Behavior Studies. *Exercise and Sport Sciences Reviews*, *43*(1), 48–56. https://doi.org/10.1249/JES.0000000000000035

Jankowska, M. M., Yang, J.-A., Luo, N., Spoon, C., & Benmarhnia, T. (2021). Accounting for space, time, and behavior using GPS derived dynamic measures of environmental exposure. *Health & Place*, *xxxx*, 102706. https://doi.org/10.1016/j.healthplace.2021.102706

Kadomura, A., Li, C.-Y., Chen, Y.-C., Tsukada, K., Siio, I., & Chu, H. (2013). Sensing fork: Eating behavior detection utensil and mobile persuasive game. *CHI '13 Extended Abstracts on Human Factors in Computing Systems on - CHI EA '13*, *2013-April*, 1551. https://doi.org/10.1145/2468356.2468634

Kestens, Y., Chaix, B., Gerber, P., Desprès, M., Gauvin, L., Klein, O., Klein, S., Köppen, B., Lord, S., Naud, A., Patte, M., Payette, H., Richard, L., Rondier, P., Shareck, M., Sueur, C., Thierry, B., Vallée, J., & Wasfi, R. (2016). Understanding the role of contrasting urban contexts in healthy aging: an international cohort study using wearable sensor devices (the CURHA study protocol). *BMC Geriatrics*, *16*(1), 96. https://doi.org/10.1186/s12877-016-0273-7

Kim, E.-K., & MacEachren, A. M. (2014). An Index for Characterizing Spatial Bursts of Movements: A Case Study with Geo-Located Twitter Data. *Workshop on Analysis of Movement Data, in Conjunction with GIScience 2014*. https://doi.org/10.13140/RG.2.1.2949.9284

Kim, J., & Kwan, M.-P. (2021). How Neighborhood Effect Averaging Might Affect Assessment of Individual Exposures to Air Pollution: A Study of Ozone Exposures in Los Angeles. *Annals of the American Association of Geographers*, *111*(1), 121–140. https://doi.org/10.1080/24694452.2020.1756208

Klaassen, B., van Beijnum, B. J. F., & Hermens, H. J. (2016). Usability in telemedicine systems—A literature survey. *International Journal of Medical Informatics*, *93*, 57–69. https://doi.org/10.1016/j.ijmedinf.2016.06.004

Klein, S., Brondeel, R., Chaix, B., Klein, O., Thierry, B., Kestens, Y., Gerber, P., & Perchoux, C. (2021). What triggers selective daily mobility among older adults? A study comparing trip and environmental characteristics between observed path and shortest path. *Health & Place*, *November*, 102730. https://doi.org/10.1016/j.healthplace.2021.102730

Kumar, D., Jeuris, S., Bardram, J. E., & Dragoni, N. (2021). Mobile and Wearable Sensing Frameworks for mHealth Studies and Applications. *ACM Transactions on Computing for Healthcare*, *2*(1), 1–28. https://doi.org/10.1145/3422158

Kwan, M.-P. (2012). The Uncertain Geographic Context Problem. *Annals of the Association of American Geographers*, *102*(5), 958–968. https://doi.org/10.1080/00045608.2012.687349

Kwan, M.-P. (2018). The Limits of the Neighborhood Effect: Contextual Uncertainties in Geographic, Environmental Health, and Social Science Research. *Annals of the American Association of Geographers*, *108*(6), 1482–1490. https://doi.org/10.1080/24694452.2018.1453777

Lee, J. H., Davis, A. W., Yoon, S. Y., & Goulias, K. G. (2016). Activity space estimation with longitudinal observations of social media data. *Transportation*, *43*(6), 955–977. https://doi.org/10.1007/s11116-016-9719-1

Li, B., Quader, I. J., & Dempster, A. G. (2008). On outdoor positioning with Wi-Fi. *Journal of Global Positioning Systems*, *7*(1), 18–26. https://doi.org/10.5081/jgps.7.1.18

Li, J., Kim, C., & Sang, S. (2018). Exploring impacts of land use characteristics in residential neighborhood and activity space on non-work travel behaviors. *Journal of Transport Geography*, *70*(June), 141–147. https://doi.org/10.1016/j.jtrangeo.2018.06.001

Liu, B., Widener, M. J., Smith, L. G., Farber, S., Minaker, L. M., Patterson, Z., Larsen, K., & Gilliland, J. (2021). Disentangling Time Use, Food Environment, and Food Behaviors Using Multi-Channel Sequence Analysis. *Geographical Analysis*. https://doi.org/10.1111/gean.12305

Lizana, M., Carrasco, J. A., & Victoriano, R. (2022). Daily activity-travel and fragmentation patterns in the weekly cycle: evidence of the role of ICT, time use, and personal networks. *Transportation Letters*, *14*(4), 396–406. https://doi.org/10.1080/19427867.2021.1879623

Long, J. A., Malekzadeh, M., Klar, B., & Martin, G. (2021). Do regionally targeted lockdowns alter movement to non-lockdown regions? Evidence from Ontario, Canada. *Health & Place*, *May*, 102668. https://doi.org/10.1016/j.healthplace.2021.102668

Luo, M., Kim, E.-K., Weibel, R., Martin, M., & Röcke, C. (2022). GPS-Derived Daily Mobility and Daily Well-Being in Community-Dwelling Older Adults. *Gerontology*.

Ma, J., Rao, J., Kwan, M.-P., & Chai, Y. (2020). Examining the effects of mobility-based air and noise pollution on activity satisfaction. *Transportation Research Part D: Transport and Environment*, *89*(November), 102633. https://doi.org/10.1016/j.trd.2020.102633

Mangalam, M., & Kelty-Stephen, D. G. (2021). Point estimates, Simpson’s paradox, and nonergodicity in biological sciences. *Neuroscience & Biobehavioral Reviews*, *125*(February), 98–107. https://doi.org/10.1016/j.neubiorev.2021.02.017

Martin, M., Weibel, R., Rocke, C., & Boker, S. M. (2018). Semantic Activity Analytics for Healthy Aging: Challenges and Opportunities. *IEEE Pervasive Computing*, *17*(3), 73–77. https://doi.org/10.1109/MPRV.2018.03367738

Mastropietro, A., Palumbo, F., Orte, S., Girolami, M., Furfari, F., Baronti, P., Candea, C., Roecke, C., Tarro, L., Sykora, M., Porcelli, S., & Rizzo, G. (2021). A multi-domain ontology on healthy ageing for the characterization of older adults status and behaviour. *Journal of Ambient Intelligence and Humanized Computing*, *0123456789*. https://doi.org/10.1007/s12652-021-03627-6

Mehl, M. R. (2017). The Electronically Activated Recorder (EAR): A Method for the Naturalistic Observation of Daily Social Behavior. *Current Directions in Psychological Science*, *26*(2), 184–190. https://doi.org/10.1177/0963721416680611

Mehl, M. R., & Conner, T. S. (Eds.). (2011). *Handbook of Research Methods for Studying Daily Life*. Guilford Press.

Miller, G. (2012). The Smartphone Psychology Manifesto. *Perspectives on Psychological Science*, *7*(3), 221–237. https://doi.org/10.1177/1745691612441215

Molenaar, P. C. M. (2004). A Manifesto on Psychology as Idiographic Science: Bringing the Person Back Into Scientific Psychology, This Time Forever. *Measurement: Interdisciplinary Research & Perspective*, *2*(4), 201–218. https://doi.org/10.1207/s15366359mea0204_1

Montoliu, R., Blom, J., & Gatica-Perez, D. (2013). Discovering places of interest in everyday life from smartphone data. *Multimedia Tools and Applications*, *62*(1), 179–207. https://doi.org/10.1007/s11042-011-0982-z

Nahum-Shani, I., Smith, S. N., Spring, B. J., Collins, L. M., Witkiewitz, K., Tewari, A., & Murphy, S.

A. (2018). Just-in-Time Adaptive Interventions (JITAIs) in Mobile Health: Key Components and Design Principles for Ongoing Health Behavior Support. *Annals of Behavioral Medicine*, *52*(6), 446–462. https://doi.org/10.1007/s12160-016-9830-8

Nguyen, M. H., Armoogum, J., Madre, J. L., & Garcia, C. (2020). Reviewing trip purpose imputation in GPS-based travel surveys. *Journal of Traffic and Transportation Engineering (English Edition)*, *7*(4), 395–412. https://doi.org/10.1016/j.jtte.2020.05.004

Olla, P., & Shimskey, C. (2015). mHealth taxonomy: a literature survey of mobile health applications. *Health and Technology*, *4*(4), 299–308. https://doi.org/10.1007/s12553-014-0093-8

ONC, (The Office of the National Coordinator for Health Information Technology). (2022). *The Office of the National Coordinator for Health Information Technology (ONC): Standards and Technology*.

Osborne, T., & Jones, P. I. (2017). Biosensing and geography: A mixed methods approach. *Applied Geography*, *87*, 160–169. https://doi.org/10.1016/J.APGEOG.2017.08.006

Park, Y. M., Sousan, S., Streuber, D., & Zhao, K. (2021). GeoAir—A Novel Portable, GPS-Enabled, Low-Cost Air-Pollution Sensor: Design Strategies to Facilitate Citizen Science Research and Geospatial Assessments of Personal Exposure. *Sensors*, *21*(11), 3761. https://doi.org/10.3390/s21113761

Perchoux, C., Chaix, B., Brondeel, R., & Kestens, Y. (2016). Residential buffer, perceived neighborhood, and individual activity space: New refinements in the definition of exposure areas – The RECORD Cohort Study. *Health & Place*, *40*, 116–122. https://doi.org/10.1016/j.healthplace.2016.05.004

Perchoux, C., Kestens, Y., Brondeel, R., & Chaix, B. (2015). Accounting for the daily locations visited in the study of the built environment correlates of recreational walking (the RECORD Cohort Study). *Preventive Medicine*, *81*, 142–149. https://doi.org/10.1016/j.ypmed.2015.08.010

Perchoux, C., Kestens, Y., Thomas, F., Hulst, A. Van, Thierry, B., & Chaix, B. (2014). Assessing patterns of spatial behavior in health studies: Their socio-demographic determinants and associations with transportation modes (the RECORD Cohort Study). *Social Science & Medicine*, *119*, 64–73. https://doi.org/10.1016/j.socscimed.2014.07.026

Plue, R., Jewett, L., & Widener, M. J. (2020). *Considerations When Using Individual GPS Data in Food Environment Research: A Scoping Review of 'Selective (Daily) Mobility Bias' in GPS Exposure Studies and Its Relevance to the Retail Food Environment* (pp. 95–112). https://doi.org/10.1007/978-3-030-19573-1_6

Poom, A., Willberg, E., & Toivonen, T. (2021). Environmental exposure during travel: A research review and suggestions forward. *Health and Place*, *70*(April), 102584. https://doi.org/10.1016/j.healthplace.2021.102584

Psyllidis, A., Gao, S., Hu, Y., Kim, E.-K., McKenzie, G., Purves, R., Yuan, M., & Andris, C. (2022). Points of Interest (POI): a commentary on the state of the art, challenges, and prospects for the future. *Computational Urban Science*, *2*(1), 20. https://doi.org/10.1007/s43762-022-00047-w

Ram, N., & Gerstorf, D. (2009). Time-structured and net intraindividual variability: Tools for examining the development of dynamic characteristics and processes. *Psychology and Aging*, *24*(4), 778–791. https://doi.org/10.1037/a0017915

Röcke, C., Luo, M., Bereuter, P., Katana, M., Fillekes, M. P., Gehriger, V., Sofios, A., Martin, M., & Weibel, R. (2022). Charting Everyday Activities in Later Life: Study Protocol of the Mobility, Activity, and Social Interactions Study (MOASIS). *Frontiers in Psychology*. https://doi.org/10.3389/fpsyg.2022.1011177

Rodriguez-León, C., Villalonga, C., Munoz-Torres, M., Ruiz, J. R., & Banos, O. (2021). Mobile and Wearable Technology for the Monitoring of Diabetes-Related Parameters: Systematic Review.

JMIR MHealth and UHealth, *9*(6), e25138. https://doi.org/10.2196/25138

Roy, A., Fuller, D., Nelson, T., & Kedron, P. (2022). Assessing the role of geographic context in transportation mode detection from GPS data. *Journal of Transport Geography*, *100*(March), 103330. https://doi.org/10.1016/j.jtrangeo.2022.103330

Salvi, D., Poffley, E., Orchard, E., & Tarassenko, L. (2020). The Mobile-Based 6-Minute Walk Test: Usability Study and Algorithm Development and Validation. *JMIR MHealth and UHealth*, *8*(1), e13756. https://doi.org/10.2196/13756

Schnell, I., Cohen, P., Mandelmilch, M., & Potchter, O. (2021). Portable - trackable methodologies for measuring personal and place exposure to nuisances in urban environments: Towards a people oriented paradigm. *Computers, Environment and Urban Systems*, *86*(December 2020), 101589. https://doi.org/10.1016/j.compenvurbsys.2020.101589

Scully, J. Y., Moudon, A. V., Hurvitz, P. M., Aggarwal, A., & Drewnowski, A. (2019). A time-based objective measure of exposure to the food environment. *International Journal of Environmental Research and Public Health*, *16*(7). https://doi.org/10.3390/ijerph16071180

Seifert, A., & Vandelanotte, C. (2021). The use of wearables and health apps and the willingness to share self-collected data among older adults. *Aging and Health Research*, *1*(3), 100032. https://doi.org/10.1016/j.ahr.2021.100032

Seneviratne, S., Hu, Y., Nguyen, T., Lan, G., Khalifa, S., Thilakarathna, K., Hassan, M., & Seneviratne, A. (2017). A Survey of Wearable Devices and Challenges. *IEEE Communications Surveys and Tutorials*, *19*(4), 2573–2620. https://doi.org/10.1109/COMST.2017.2731979

Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological Momentary Assessment. *Annual Review of Clinical Psychology*, *4*(1), 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415

Shrestha, S., Kestens, Y., Thomas, F., El Aarbaoui, T., & Chaix, B. (2019). Spatial access to sport facilities from the multiple places visited and sport practice: Assessing and correcting biases related to selective daily mobility. *Social Science & Medicine*, *236*(February 2018), 112406. https://doi.org/10.1016/j.socscimed.2019.112406

Sila-Nowicka, K., & Thakuriah, P. (2019). Multi-sensor movement analysis for transport safety and health applications. *PLOS ONE*, *14*(1), e0210090. https://doi.org/10.1371/journal.pone.0210090

Sim, I. (2019). Mobile Devices and Health. *New England Journal of Medicine*, *381*(10), 956–968. https://doi.org/10.1056/NEJMra1806949

Smith, L., Foley, L., & Panter, J. (2019). Activity spaces in studies of the environment and physical activity: A review and synthesis of implications for causality. *Health & Place*, *58*(December 2018), 102113. https://doi.org/10.1016/j.healthplace.2019.04.003

Smith, L. G., Widener, M. J., Liu, B., Farber, S., Minaker, L. M., Patterson, Z., Larsen, K., & Gilliland, J. (2022). Comparing Household and Individual Measures of Access through a Food Environment Lens: What Household Food Opportunities Are Missed When Measuring Access to Food Retail at the Individual Level? *Annals of the American Association of Geographers*, *112*(2), 542–562. https://doi.org/10.1080/24694452.2021.1930513

Tao, Yaguang, Both, A., Silveira, R. I., Buchin, K., Sijben, S., Purves, R. S., Laube, P., Peng, D., Toohey, K., & Duckham, M. (2021). A comparative analysis of trajectory similarity measures. *GIScience & Remote Sensing*, *58*(5), 643–669. https://doi.org/10.1080/15481603.2021.1908927

Tao, Yinhua, Chai, Y., Zhang, X., Yang, J., & Kwan, M. P. (2021). Mobility-based environmental justice: Understanding housing disparity in real-time exposure to air pollution and momentary psychological stress in Beijing, China. *Social Science and Medicine*, *287*(May), 114372. https://doi.org/10.1016/j.socscimed.2021.114372

Tedesco, S., Sica, M., Ancillao, A., Timmons, S., Barton, J., & O'Flynn, B. (2019). Validity Evaluation of the Fitbit Charge2 and the Garmin vivosmart HR+ in Free-Living Environments in an Older Adult Cohort. *JMIR MHealth and UHealth*, *7*(6), e13084. https://doi.org/10.2196/13084

Thierry, B., Chaix, B., & Kestens, Y. (2013). Detecting activity locations from raw GPS data: a novel kernel-based algorithm. *International Journal of Health Geographics*, *12*(1), 14. https://doi.org/10.1186/1476-072X-12-14

Timmons, A. C., Baucom, B. R., Han, S. C., Perrone, L., Chaspari, T., Narayanan, S. S., & Margolin, G. (2017). New Frontiers in Ambulatory Assessment: Big Data Methods for Capturing Couples' Emotions, Vocalizations, and Physiology in Daily Life. *Social Psychological and Personality Science*, *8*(5), 552–563. https://doi.org/10.1177/1948550617709115

Van Cauwenberg, J., Nathan, A., Barnett, A., Barnett, D. W., & Cerin, E. (2018). Relationships Between Neighbourhood Physical Environmental Attributes and Older Adults' Leisure-Time Physical Activity: A Systematic Review and Meta-Analysis. *Sports Medicine*, *48*(7), 1635–1660. https://doi.org/10.1007/s40279-018-0917-1

Vogels, E. A. (2020). *About one-in-five Americans use a smart watch or fitness tracker*. https://www.pewresearch.org/fact-tank/2020/01/09/about-one-in-five-americans-use-a-smart-watch-or-fitness-tracker/

Wang, J., Kwan, M.-P., & Chai, Y. (2018). An Innovative Context-Based Crystal-Growth Activity Space Method for Environmental Exposure Assessment: A Study Using GIS and GPS Trajectory Data Collected in Chicago. *International Journal of Environmental Research and Public Health*, *15*(4), 703. https://doi.org/10.3390/ijerph15040703

WHO, (World Health Organization). (2011). *mHealth: New Horizons for Health through Mobile Technologies: Based on the Findings of the Second Global Survey on eHealth* (No. 3).

Wray, A., Martin, G., Doherty, S., & Gilliland, J. (2021). Analyzing differences between spatial exposure estimation methods: A case study of outdoor food and beverage advertising in London, Canada. *Health & Place*, *July*, 102641. https://doi.org/10.1016/j.healthplace.2021.102641

Yan, Z., Chakraborty, D., Parent, C., Spaccapietra, S., & Aberer, K. (2013). Semantic trajectories: Mobility Data Computation and Annotation. *ACM Transactions on Intelligent Systems and Technology*, *4*(3), 1–38. https://doi.org/10.1145/2483669.2483682

Yoo, E., Roberts, J. E., Eum, Y., & Shi, Y. (2020). Quality of hybrid location data drawn from GPS-enabled mobile phones: Does it matter? *Transactions in GIS*, *24*(2), 462–482. https://doi.org/10.1111/tgis.12612

Zhang, R., Stanley, K. G., Bell, S., & Fuller, D. (2018). A feature set for spatial behavior characterization. *Proceedings of the 26th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, 512–515. https://doi.org/10.1145/3274895.3274973

Zhao, Q., Li, Z., Shah, D., Fischer, H., Solís, P., & Wentz, E. (2021). Understanding the interaction between human activities and physical health under extreme heat environment in Phoenix, Arizona. *Health & Place*, *March*, 102691. https://doi.org/10.1016/j.healthplace.2021.102691