Chapter 17
Urban Health and Wellbeing

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Abstract This chapter explores how the Internet of Things and the utilization of cutting-edge information technology are shaping global research and discourse on the health and wellbeing of urban populations. The chapter begins with a review of smart cities and health and then delves into the types of data available to researchers. The chapter then discusses innovative methods and techniques, such as machine learning, personalized sensing, and tracking, that researchers use to examine the health and wellbeing of urban populations. The applications of these data, methods, and techniques are then illustrated taking examples from BERTHA (Big Data Centre for Environment and Health) based at Aarhus University, Denmark. The chapter concludes with a discussion on issues of ethics, privacy, and confidentiality surrounding the use of sensitive and personalized data and tracking or sensing individuals across time and urban space.

17.1 Smart Cities and Health

Smart cities have become popular in urban discourse, research, and policy environments; yet the term remains ambiguous. Here, we conceptualize smart cities as enabled by the Internet of Things (IoT), where sensing citizens and authorities employ information and technology to better navigate their lives and manage resources more

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efficiently. The utilization of information technology presents unique opportunities for understanding individual behavior and interactions in the urban space and their implications for human health and wellbeing. Often the aim is to combine the use of digital technologies and green city planning to optimize wellbeing and at the same time improve the physical environment and mitigate climate change. Boulos and Al-Shorbaji (2014) assert that an important component of smart cities is that they contain the ingredients necessary for improving the quality of life and wellbeing of residents. The technology and information available to urban residents have the potential to affect their health positively or negatively.

On the one hand, technology and the interconnection of people via the Internet present the opportunity for increasing access to health and health-enhancing information while reducing the cost of health care, particularly for the socioeconomically vulnerable (Aborokbah et al. 2018; Solanas et al. 2014). Remote monitoring of individuals can help quantify individual-level risks and provide vital information for effective person-centered health care (Aborokbah et al. 2018). For instance, real-time individual physiological and environmental information could help healthcare providers understand contextual factors that expose an individual to adverse health outcomes or improve their health and psychosocial wellbeing (Bryant et al. 2017; Lomotey et al. 2017; Rocha et al. 2019).

Others talk about the use of technology and information to deliver services to vulnerable and disadvantaged persons in the urban context with the aim of increasing their independence and wellbeing (Gilart-Iglesias et al. 2015; Rodrigues et al. 2018; Turcu and Turcu 2013). Just as studies show the myriad advantages associated with using personal information and technology in advancing health and wellbeing, they also highlight their negative effect on health outcomes (Do et al. 2013). The use of the Internet has opened new health and wellbeing challenges, beyond the traditional methods of providing and sustaining health and wellbeing, including misinformation, cyberbullying, cyber-fraud, and victimization. Do et al. (2013) observed that excessive use of the Internet among adolescents contributes to a higher incidence or likelihood of reporting depressive symptoms, suicidal thoughts, overweight, and lower self-reported health status due to sleep deprivation. Likewise, studies also show that the Internet has given an impetus to anti-vaccination campaigns through misinformation, contributing to lower acceptance and hesitation in accepting vaccine (Dubé et al. 2014).

This chapter is structured into four main sections, all considering health and wellbeing in an urban context. We begin by discussing data in an informatics era, before considering existing and emerging analytical techniques and methods. Example applications are taken from our BERTHA center, before we round off the discussion with the important issues surrounding privacy and confidentiality.

BERTHA (Big Data Centre for Environment and Health) is our interdisciplinary research center, based at Aarhus University, Denmark, bringing together urban geographers, environmental modelers, data scientists, and medical practitioners. BERTHA aims to muster the huge potential opportunities from the big data revolution in medical, environmental and population registers, personalized sensors, and crowdsourced data mining to disentangle the complex interactions between whole-life-course environmental and social exposures, and human health. Key to this overarching aim is assembling, linking, and analyzing diverse, huge datasets, developing algorithms, and intelligent data analytics.

17.2 Data

17.2.1 Big Data

There has been a lot of hype and hyperbole in the past decade over the Big Data paradigm. Big Data from a variety of data sources from government and citizens can be applied to improve urban health and wellbeing (Fleming et al. 2014). Within BERTHA, we see Big Data as not just about using large datasets, but critically, the combination of (huge) datasets to reveal value greater than the sum of the individual parts. The Big Data term has also been used to encompass the use of predictive data analytics and the computational analysis of extremely large, multi-source datasets to reveal patterns, trends, and associations. Thus, we prefer Rich Data rather than Big Data.

17.2.2 Individual and Population Data

Decisions on the health and wellbeing of a population are often informed by data and knowledge available on individual citizens. Generally, there are two sources of data for this decision-making process: individual or population data, and environmental data. Traditionally, administrative records and censuses were the main sources of individual or population-level data. While these data sources have their flaws, the data from some countries, including the Scandinavian countries, contain rich information about individuals from the onset of their lives till their demise (Frank 2000). The data from these registers enable detailed analyses and research on each individual in the population. The information from the various registers can be linked to each member of the population through a unique personal identification number. Examples of such unique identification numbers are Denmark's Centrale Personregister (Central Person Register, CPR) number, Norway's Fødselsnummer (national identification number), and Sweden's personnummer. In Denmark, these unique identifiers enable researchers to link data and information from nearly 200 databases from information on places of residence, employment, to medical records and socioeconomic data on salaries and tax. The records of some databases extend as far back as 1924 (Pedersen 2011; Pedersen et al. 2006), but the critical ones have been digital since 1968. In other countries, the information about individuals from government registers and databases can be extracted or linked using social-security numbers; for example, Canada's Social Insurance Number (SIN). Similar to the Scandinavian personal identification numbers, these unique social-security numbers are normally assigned at birth. Information from the registers and the databases, such as a residential address, workplace, and school, can also be geocoded, enabling researchers to identify environmental exposures over each individual's total life course (Pedersen 2011). Particularly in the case of the data from Scandinavian registers, it is possible to define location histories of each individual in the population, accurately georeferenced to 1 m (Pedersen 2011).

In the digital era, tracking and sensing of an individual's activities in urban environments has become commonplace (Lupton 2013, 2017; Swan 2009, 2012). Advances in technology and miniaturization have facilitated the ability to track time-activity patterns of individuals, via GPS-enabled smartphone apps, watches, or proprietary wearable devices. These digital devices and social-media platforms not only enable individuals to generate and analyze personalized health data, but also enable them to share this information directly or indirectly with others (Gimpe et al. 2013; Lupton 2013, 2017). Prior to this, the accepted practice was to use daily research diaries to record life events and activities. These diaries may be intimate journals with uncensored information about one's thoughts, opinions, or experiences; or memoirs often written with an audience in mind; or a log of events and activities that occurred in one's life (Elliott 1997).

17.2.3 Environmental Data

Records of air pollution, water quality, housing conditions, recreational space, and exposure to chemicals traditionally came from field surveys, household surveys, or stationary observations. However, these data are usually limited in sample size and are not often available for longitudinal studies. Increasingly, environmental data are obtained from modeling or simulation, informed from field monitoring.

Remote sensing is a valuable source of environmental data, which are complementary to survey data and help to capture the dynamics of urban environments. Time-series satellite images allow understanding of urban sprawl and shrinkage in many parts of the world. For instance, urban expansion has been investigated with Landsat time-series images over more than two decades in India (Sharma and Joshi 2013), the USA (Li et al. 2018; Sexton et al. 2013), Japan (Bagan and Yamagata 2012), and China (Shi et al. 2017). The variations of urban greenness across the years can also be monitored via remote-sensing data and used to predict the outbreaks of mosquito-borne diseases in cities (Chen et al. 2018). On the other hand, building damage and land-use changes due to environmental disturbances, such as the 2003 Bam earthquake in Iran (Chini et al. 2008) and the 2011 Fukushima nuclear disaster in Japan (Sekizawa et al. 2015), were traced by satellite. In complex human-environment systems, researchers also utilize satellite images to understand different pathways of agricultural damage (Chen and Lin 2018).

Many recent epidemiological studies have evaluated the health impacts of specific land-cover types and the configuration of urban land use, including commercial, residential, and recreational areas, green space, agricultural areas, and proximity to blue space. The literature shows that natural environments, such as green or blue space, can have health-enhancing (or salutogenic) properties that improve the physical and psychosocial wellbeing of urban residents (Bornioli et al. 2018; Duarte et al. 2010; Olsen et al. 2019; Stigsdotter et al. 2017); however, the associations between environmental measures and health remain uncertain (Briggs et al. 2009; Wheeler et al. 2015). Other studies have questioned the relationship between salutogenic spaces and health outcomes (Gren et al. 2018). For instance, while green space may mitigate pollution levels through removing pollutants from the air, it is also a source of pollens, aggravating allergies and increasing particulate-matter counts.

Researchers have also been critical of the proxies used in measuring environmental exposures. Determining exposure metrics of various land covers that potentially impact health is complex. Early work (Pearce et al. 2006) used distance as a proxy for exposure to green space, by defining either a radius around the residential home or using the road network distance. Nearly, all studies have focused on the residential home, or neighborhood, as the location of analysis, often ignoring places of work or education and the more complex daily-life trajectories (Sabel et al. 2000, 2009; Steinle et al. 2013). However, proximity does not equate to accessibility. The literature highlights the distinction between the two concepts and stresses that physical and socioeconomic barriers (including, highways, or gated communities) may impede the ability of individuals in proximity to these natural environments from fully benefitting from their health-enhancing properties (Markevych et al. 2017). More recently, research has moved on to consider the quality and configuration of urban space, since there is evidence that homogeneous spaces are less beneficial to health than heterogeneous, biodiverse ones (Wheeler et al. 2015).

Air pollution is traditionally measured by costly devices at fixed-site monitoring stations. It is absolutely crucial that such devices are advanced and accurate, since they are usually used in air-pollution monitoring programs legislated by governments to test compliance with air-quality guidelines. However, it is increasingly being questioned whether assessing personal exposure to air pollution using fixed-site monitoring data might provide an error in the individual exposure as the impact of the mobility pattern is ignored (Buonanno et al. 2014; Steinle et al. 2013). However, newly developed low-cost, portable sensor nodes provide new options for personal-exposure monitoring (PEM) by mobile measurements. The sensor nodes can easily be carried around during our daily life, where we constantly move in time and space through different environments both indoor and outdoor. We commute between home and work, spend time indoors with household activities and work, and maybe we play with our kids at the local playground. Thus, we are constantly exposed to highly variable concentrations of air pollution with documented evidence for negative health effects. However, these low-cost personal air-pollution sensors are not as robust scientifically as the fixed-site monitors, and it is still uncertain how measurements are affected when the sensor nodes are moving: how does it affect the performance of the sensors when one moves between different microenvironments, especially when one moves from indoors to outdoors, exposing the sensor to rapid changes in temperature and humidity.

17.3 Methods and Techniques

Recent advances in information technology have contributed new sources of individual data for researchers in their quest to understand human-environment interactions and their impact on health and wellbeing in urban space. Mobile digital devices, such as smartphones, smartwatches, tablets, and sensors, together with apps on the devices, can collect users' data on physical activity, sporting performance, and daily routines, as well as demographic and health data. These mobile devices also simultaneously provide spatiotemporal geolocational data of the user, using GPS or cellphone-network triangulation. The information from these devices has radically changed the opportunities for researchers and practitioners within the health and wellbeing arena. For researchers, it has extended the traditional boundaries and the methods, techniques, or approaches used in conducting our studies; and also makes us critical of existing models and concepts of health and wellbeing (Lupton 2013; Swan 2009). For medical practitioners, the data can provide additional information about patients, the inclusion of the individual in the healthcare process, and the ability to provide holistic care for patients (Dingler et al. 2014).

Compared with traditional methods, multi-source big data could be collected from many other aspects passively and unconsciously. Wang et al. (2019a, b) in their survey about sensor-based human activity recognition (HAR) catalog common-used sensors into four types: (1) Inertial sensors, including accelerometer, gyroscope, and magnetometer applied in detecting multiple motions; (2) Physical health sensors, such as electrocardiograms, skin temperature, heart rate, and force sensors, used to detect people's health conditions, while new technology products like sports watches and fitness tracking bracelets have a similar function; (3) Environmental sensors like temperature, light, and barometer sensors, delivering context information related to activities; (4) Others: other wearable devices like cameras, microphones, and GPS. GPS can track people's routes and record locations simultaneously and is useful in studies of urban space and people's behavior (Bohte and Maat 2009). The cell phone has been applied in public-health studies and can be combined with gyroscope (Shoaib et al. 2014) and barometer (Muralidharan et al. 2014) to identify physical activity and sleep quality. Image sensors like wearable cameras have been applied in recording people's daily exposure (Wang and Smeaton 2013), including dietary intake (Zhou et al. 2019), and environmental exposure (Chambers et al. 2017).

The emergence of social media and smartphone technologies more generally has opened new sources of data for understanding health and wellbeing in the urban context. However, the data from these sources are subject to potential biases since users are often not fully representative of society, under-representing persons of lower socioeconomic status, and older and non-tech savvy persons. It can be argued that socioeconomic factors are as important as the physical environment in determining health impacts on human populations, since a disproportionate share of the burden of environmental exposure falls on vulnerable groups of society, including low SES, ethnic minorities, women, and the elderly and young, due partly to issues of environmental (in)justice. In addition, SES can explain differences in external exposure because of the different prevalence of specific behaviors in some groups; for example, differences in diet between SES groups. Individual health and wellbeing are influenced by many factors including past and present behavior, healthcare provision, and wider determinants including social, cultural, and environmental factors. Traditional sources of data, such as government registers, and demographic and health surveys, offer information on these broader contextual factors that are often absent in individual data from smart technologies. The breadth of the traditional data means they are relatively less susceptible to selection bias compared to the new sources of data.

Additionally, traditional data also bring the ability to construct area-level exposures and their influence on health and wellbeing, such as to address the context versus composition debate (Macintyre et al. 2002), regarding the wider question of which is more important for shaping health: the area in which people live (context) or the people who make up the inhabitants of that area (composition). Area-level SES is often estimated by means of a weighted index of factors from published secondary data, such as the UK Index of Multiple Deprivation (IMD) and the Vancouver Area Neighborhood Deprivation Index (VANDIX) (Bell and Hayes 2012; Ellaway et al. 2012; Macintyre et al. 2008; Schuurman et al. 2007). Weighted factors might typically include measures of education, income, homeownership, and access to transport.

Another informatics area experiencing fast adoption is using citizens as sensors (Goodchild 2007) to obtain evidence of citizens' experiences in the urban landscape (Zook 2017). An emerging field in the health arena, supported by smartphone technology, is ecological momentary assessment. Here apps are utilized such as in the Mappiness project (MacKerron and Mourato 2013; Seresinhe et al. 2019) to ask people to describe their responses to the environment directly, with the advantage that input is related to the current location via GPS. This allows researchers to explore the more psychological aspects of how people are responding to their environments.

Modeling, as opposed to monitoring, of urban environments has been enabled by the digital era. As a branch of artificial intelligence, machine learning is a field of study growing in popularity in urban modeling that provides computers with the ability to automatically learn and improve their own algorithms from data. Machine-learning studies often investigate urban dynamics based on remotely sensed data. The approach of mapping the urban environment with machine-learning methods goes back to the 1990s. For instance, Gong et al. (1992) used a maximum-likelihood classifier and USGS Landsat imagery to automate urban land-use mapping. Such development, however, was slow until the 2000s, when satellite images at 30 m and finer resolution became affordable and publicly readable (Weng 2012).

Machine learning has the potential to automate the process of urban mapping, which traditionally relies on intensive labor. Automatic image recognition, from sources such as Google Streetview, encourages urban scientists to detect more nuanced features in cities. With the capability of increasing computation power, deep-learning methods, such as convolutional neural networks (CNNs), have increased the dimension of detectable urban attributes. Because of CNN's capabilities in recognizing the spatial patterns of image patches, recent studies have applied CNN to streetview images and aerial photographs for quantifying a sky view of street canyons (Gong et al. 2018), mapping local climate zones (Qin et al. 2017), and classifying specific types of urban facilities (e.g., church, park, and garage) (Kang et al. 2018). Remote sensing and machine learning are complements to urban simulation models (Batty 2013), which can forecast dynamics and growth, but not represent spatial details.

Similarly, researchers have also applied machine-learning methods to data from personalized sensors and streetview images to understand dynamism in the urban space and its effect on mental health as well as susceptibility to crime (Goin et al. 2018; Helbich 2018; Helbich et al. 2016; Mohr et al. 2017; Wang et al. 2019a, b). Machine learning can also be used to improve the prediction accuracy of models that seek to understand the effect of individual and community factors on health outcomes. Machine-learning approaches, such as least absolute shrinkage and selection operator (LASSO) and random forest, have been used to identify optimal individual-level and community-level factors that predict firearm violence in urban communities (Goin et al. 2018).

17.4 BERTHA Studies

17.4.1 AirGIS

Models are used in academic research to enhance our knowledge of reality by simplifying the complexity of the phenomena we study as researchers. For instance, GIS models are used to estimate and assess exposure to adverse environmental conditions. In Denmark, the Danish AirGIS (Jensen et al. 2001) and Operational Street Pollution Model (OSPM) (Berkowicz 2000) are routinely used to estimate street- or local-scale air pollution. In an effort to improve this model system and increase its accessibility, researchers in BERTHA developed an open-source GIS model for computing local-scale air-pollution estimates (Khan et al. 2019a, b). The new model is able to reproduce both temporal (correlation range: 0.45–0.96) and spatial (correlation range: 0.32–0.92) variations in observed air pollution, and subsequently to estimate both short- and long-term exposures to air pollution, which enables researchers to better understand its duration and effects on human health and wellbeing. The AirGIS system is currently being extended to estimate noise mainly originating from urban transport.

At present, the AirGIS is being further extended to estimate dynamic time-activity exposure to air pollution by tracking individuals in urban commuting environments, and making use of measured and modeled air-pollution data (Khan et al. 2019a,

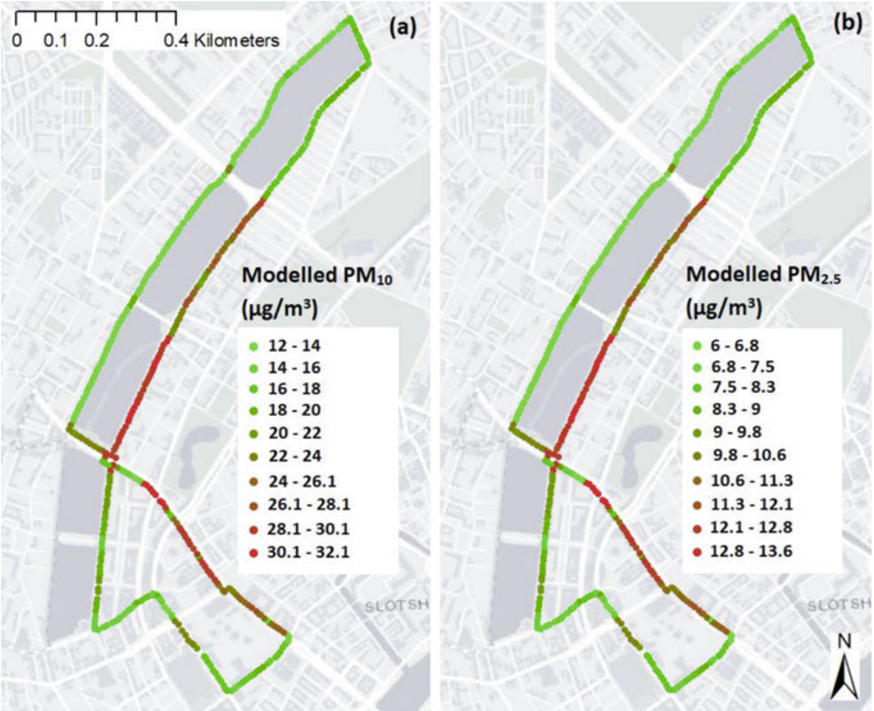

Fig. 17.1 **a** Modeled PM10 (μg m^{-3}) at GPS track points of the walking-based activity of the study participants in Copenhagen, Denmark. The modeled values are for Monday, February 4, 2019, during 7:00–10.00 am **b** the same for modeled PM2.5 (μg m^{-3})

b). The focus is on developing a novel exposure assessment framework to facilitate health-related studies. As an example a walking-based activity was performed in Copenhagen, Denmark (Khan et al. 2019a, b). At GPS track points, air-pollution concentrations (NO_x, NO_2, PM10, and PM2.5 in μg m^{-3}) were calculated using the AirGIS system to analyze dynamic exposure to modeled air pollution (Fig. 17.1). Preliminary findings suggest that exposure estimates based on time-activity patterns of individuals depend on the level of one's mobility as well as on the location of one's workplace relative to home.

17.4.2 Personalized Tracking and Sensing

Wearable devices are practically ubiquitous in the informatics era. Among these devices, the wearable camera has attracted increasing attention, since it can capture details of daily life by images or videos, which can enhance researchers' understanding of people's movements, behaviors, and preferences. Zhang and Long (2019)

Fig. 17.2 Wearable camera (also appears in Zhang and Long 2019)

conducted research in Beijing, validating applying wearable cameras (Fig. 17.2) in built-environment studies. Through identifying and analyzing 8598 images collected from a one-week experiment, they summarized the spatiotemporal characteristics of the user while wearing the camera, and compared the frequency of greenery (the ratio of green) and outdoor exposure (the ratio of blue) by means of color identification. The images were classified using artificial intelligence, and common image elements (tags) were identified (Zhang and Long 2019), including building, traffic, figure, food, digital screen, and greenery. Results showed that as a kind of digital lifelogging, an individual image database is an effective support for future interdisciplinary studies involving the environment and personal wellbeing from a micro-scale perspective. In the future, as the popularization of IoT technology becomes real, an increasing number of wearable gadgets such as wristbands (pulse, blood pressure, and heartbeat), glasses (eyesight, eye pressure, distance to screen) and so on, can be utilized to build a more comprehensive profile of individual health and exposure.

17.4.3 Personalized Air-Pollution Sensors

Computer and sensor technologies have developed tremendously over the past ten years, and air-pollution sensors have been miniaturized, are reasonably accurate, cheap, and have a fine time resolution. This development enables personal-exposure monitoring, and deploying such measurements might improve our knowledge about how we are exposed to air pollution during our regular activities. However, personalized sensors require a user-friendly interface to ease their use by those who wish to monitor their daily exposures. This is often done by visualizing data via an app. However, the design of such apps demands that some decisions be made in advance. How much information should the user of the app be presented with and how are data visualized in the most useful way? Will the idea of using different color zones make air-pollution data more understandable or will it misinform; for example, if green, yellow, and red are used to indicate low, medium, and high concentration ranges, then there is a risk that the color red will scare the user and that the color green will

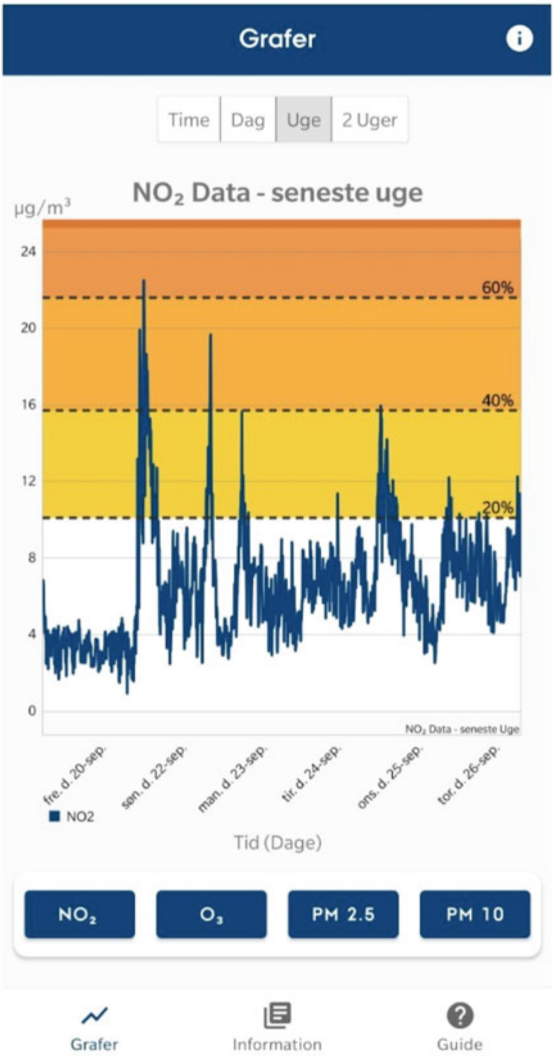

Fig. 17.3 User interface of personalized air-pollution monitoring app

misinform, as low concentrations do not necessarily mean a healthy environment. Another important thought is whether GPS positions are presented or not and how are these are secured in accordance with the EU's General Data Protection Regulation (GDPR). Our work with the personalized air-pollution sensors focuses on optimizing sensor performance in a mobile environment, along with app development to convey data to the users (Fig. 17.3).

17.4.4 Mental Health

In a nationwide study, researchers in BERTHA have combined data from the Danish Psychiatric register and green space, measured by NDVI from 30 m by 30 m Landsat imagery, in Denmark from 1985 to 2013 in order to understand the potential effect of green space exposure on schizophrenia. The study reveals that individuals with childhood exposure in places with the lowest amount of greens pace have an increased risk (1.52-fold) of developing schizophrenia (Engemann et al. 2018, 2019). From Fig. 17.4, the relative risk of schizophrenia was shown to be higher among persons in urban areas, especially in the capital (Copenhagen) compared to people living in similar NDVI deciles in other regions of the country.

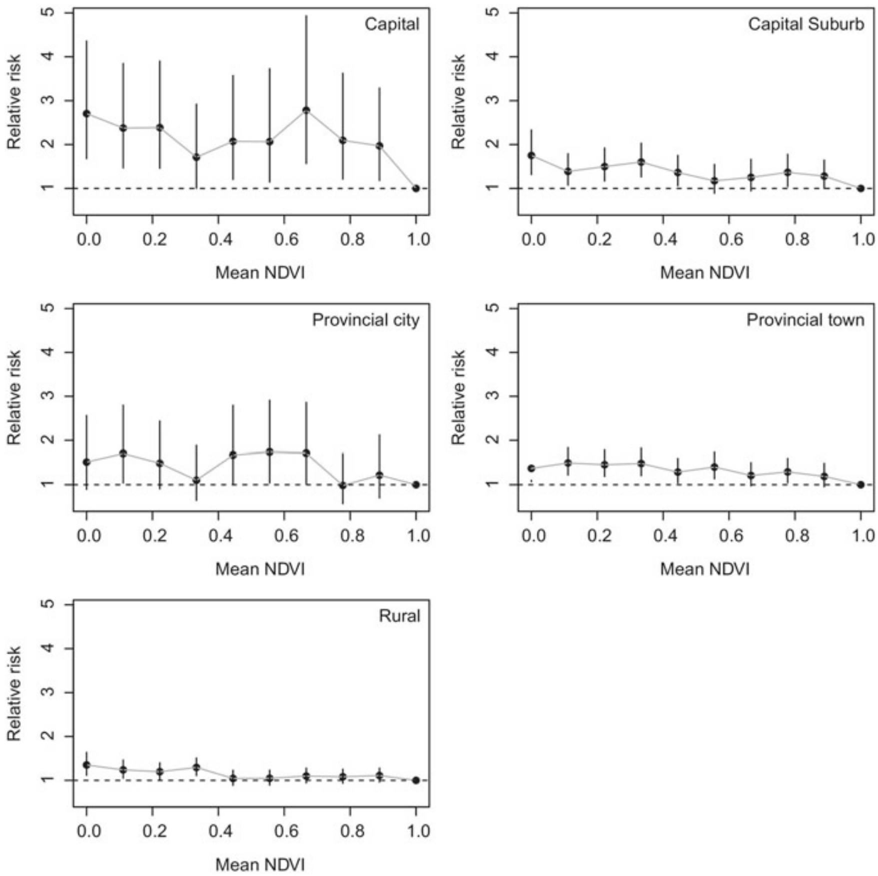

Fig. 17.4 From Engemann et al. (2018)

Further ongoing work is investigating a broader range of psychiatric disorders and natural environment exposure. Initial results suggest that growing up in natural environments is associated with lower levels of psychiatric disorders.

17.4.5 Physical Activity

BERTHA collaborates with RUNSAFE,[1] a non-commercial, multidisciplinary research group based at Aarhus University Hospital, Denmark. In collaboration with Garmin, RUNSAFE has launched a worldwide study recruiting runners willing to monitor their running habits with a Garmin device and report their injury and health status on a weekly basis over an 18-month period. With other big data, the relationship between running activity, personal characteristics, and risk of running-related injuries will be investigated (Nielsen et al. 2019). This data source is fundamental for BERTHA, as the fitness data will be combined with air pollution data to investigate if physical activity in polluted areas increases the risk of heart-rate variability as a sign of effects of air quality on the cardiovascular system.

17.4.6 Danish Blood-Donor Study

In combination with personal sensors, we are aiming at a study examining the obstacles and drivers of mobility in different age groups with a special interest in life periods—children, teenagers, adults, and seniors—as mobility has been shown to differ between these groups. The Danish blood-donor study is targeting susceptibility factors related to air pollution, taking advantage of the repetitive sampling of plasma. This enables the study of biomarkers of air pollution in the total population, or strata related to genetic markers of susceptibility, for example, atopy, gender, and age (Hansen et al. 2019).

17.5 Privacy

We live in an increasingly monitored world. People can be tracked as they navigate their urban lives, via cameras, monitoring of their smartphones, or their social media accounts. Norms and expectations are rapidly evolving. What might be considered ethically acceptable by young people might be viewed as intrusive for older generations. While this offers the urban researcher unparalleled data access, there are important ethical issues to be considered. Particularly in the health and wellbeing

[1] Garmin RunSafe: Running Health Study (n.d.) Retrieved October 7, 2019. https://garmin-runsafe.com/.

domain, there are multiple privacy issues to consider. Some of these have been covered in other chapters, notably Chap. 32, but there are specific issues to consider when handling personal health information.

Taking the example of Denmark, but similar procedures apply elsewhere, access to all individual-level data is regulated by Danish legislation. Research studies needing additional information directly from study participants also need approval from the relevant ethical committee, followed by informed consent from study participants. Updated individual-level information originating from national registers may only be accessed at secure research platforms, including Statistics Denmark or the Danish Health Data Authority. All data must comply with the recently introduced EU GDPR Regulation 2016/679 (General Data Protection Regulation).

Standard epidemiological protocols around ethics, privacy, and confidentiality also apply to data derived from personalized sensors and smartphone apps. Online consent is normally sought, for example, when users sign up to a new service, be it a wearable device or a social-media account. When users sign up, are the users aware of exactly what they are consenting to? Most apps or devices cannot be used without agreeing to the often long list of terms and conditions, and many users will not read the full terms. Once signed up, often the terms and conditions allow the service provider or sensor developer to store, analyze, make public, or sell for profit, an individual's data. Researchers can then legally access these data, often without the individual's knowledge. This is particularly challenging in a big data environment, when users might have given consent individually but may not be aware of the ability to link data across platforms to infer much more.

Lastly, the public debate around data privacy needs to balance the individual's right to privacy versus the opportunities to make new scientific discoveries from wider data availability. Globally, governments are leaning more toward the protection of citizen's rights over the exciting opportunities that wider data access could offer to make fundamental scientific breakthroughs.

17.6 Conclusions

This chapter started by sketching the relationship of smart cities and urban informatics to human health and wellbeing. We talked about the how advancement in information technology and mobile devices has enhanced health and wellbeing for urban residents through the provision of person-centered solutions to understand how the social and built environment impacts their lives. The technology and its associated platforms offer less costly ways for delivering vital health and wellbeing services to the wider population at a minimal cost. They have also encouraged individuals to be proactive participants in the healthcare delivering system, as well as offered them resources for engaging in healthy lifestyles via tracking their health behavior. Nevertheless, the emergence of these innovative and smart technologies is not without caveats. Within a rapidly changing technological world, researchers and policy-makers have to keep abreast of changing behavior and the preferences of the population, particularly the urban population who are often at the forefront of this technological drive. IoT has also exposed people to new forms of health risks, such as cyber victimization, misinformation, and addiction. As researchers, we need to develop new tools and techniques (beyond the traditional ones) to understand these risks and their implications on individuals and the wider population. Researchers and policymakers also have to maintain a delicate balance between the desire to improve health and wellbeing (using the newly available technology and data), and respecting individual privacy (and other ethical considerations). Considering the sociodemographic characteristics of users of these smart devices and technology, critical questions also remain about whether the research will perpetrate inequalities in the urban space through the policy and planning of health and wellbeing that emerge from the new IoT.

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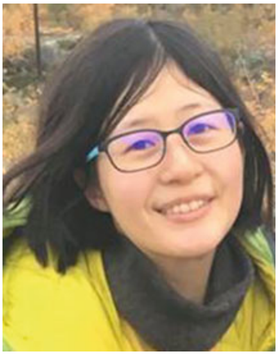

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