Chapter 7
Big Data for Urban Health and Well-Being

7.1 Introduction

The global healthcare system is already under stress from the rise in population longevity and healthcare costs, as discussed in Chap. 2. But further threats to health could come from on-going climate changes and the rise (or re-emergence) of new diseases. Ford et al. [35] have discussed the potential role for the judicious use of big data—alongside the continued use of 'small data'—for managing the risks from climate change. Big data sets can be used to provide early warning for disease outbreaks or natural disasters, for example by using social media for early warnings of storms or earthquakes. But social media data can also be mined so that emergency relief agencies can determine which areas were the most severely damaged. Also of interest is determining how the general public respond to official warnings for hazards, which can be used for their improvement. Mobile phone records and social media could be used to track the movement of people in the affected area both before and after a severe storm, for example, to gauge which type of warnings were the most effective [35].

Chapter 2 discussed the various health and well-being problems facing urban residents and showed that they could be very different for residents in high-, middle-, or low-income cities. In this chapter, we first discuss the potential for big data to improve health and well-being in OECD countries and follow with examples of its applications that have been implemented, are being trialled, or are planned. Next, we discuss the Quantified Self (QS) movement in OECD countries and the possible role in future healthcare of QS or similar trends. We then examine the potential role of big data approaches in industrialising countries—and give some examples of applications that have already been implemented or trialled—stressing that the barriers to its successful implementation may be greater than in OECD countries. We finish with a case study, which could serve as an example of QS-type approaches, and then discuss how the data generated could be used in medical research.

S. J. Wang and P. Moriarty, *Big Data for Urban Sustainability*,
https://doi.org/10.1007/978-3-319-73610-5_7

7.2 The (Contested) Potential for Big Data in OECD Healthcare

The future role of big data in health care is contested. Some observers, while aware of teething problems, feel that big data will transform both medicine and healthcare in OECD countries as well as lowering costs [9, 27, 57, 63, 70, 75, 80]. McKinsey and Company, in a report with a health industry focus, have even written about 'The 'big data' revolution in healthcare', and claimed that a tipping point is near [39]. Similarly, a *Nature* editorial [5] stressed not only the potential for big data but also the problems that must be overcome, such as the shortage of medical data scientists needed to realise its healthcare potential. The editorial pointed out the huge volumes of medically relevant data likely to be available in future, with an estimate that 'clinical data from a single individual will generate 0.4 terabytes of information per lifetime, genomics data around 6 terabytes and additional data, 1,100 terabytes.' Like other researchers (e.g. [49, 53, 85]), the editorial stressed the danger of large data sets producing spurious correlations. As Muin Khoury and John Ioannidis [49] put it: 'Paradoxically, the proportion of false alarms among all proposed 'findings' may increase when one can measure more things'. Given that Ioannidis [47] has already argued that most medical research findings, even in top quality journals, are likely to be in error, this is a serious problem.

Nitesh Chawla and Darcy Davis [22] have pointed that despite the remarkable advances in genomics and collection of huge volumes of medical data, we still lack a systems view of various diseases. They advocated a personalised healthcare approach, but not necessarily one based on genomics, and stressed that *context* is crucial for understanding diseases and their treatment and that diseases result 'from an interaction between genetic, molecular, environmental, and lifestyle factors.' They therefore argued that personalising healthcare requires developing a disease risk profile for each patient, not only by using that patient's (electronic) medical record but also by looking for 'similarities of that patient to millions of other patients.' This approach to personalised healthcare would thus be based on data mining [44].

As shown in Sect. 2.1, a key concern for future healthcare provision in all countries is its rising costs; costs are even rising as a share of GDP. For the US, one estimate for the early 2010s was $ 2.6 trillion, 75% of which was for chronic disease management [77]. One important possible justification for using the huge data volumes generated is thus the potential for cost savings. In 2005, researchers at the RAND Corporation estimated that, *provided certain conditions were met*, 'rapid adoption of health information technology (IT) could save the United States more than $81 billion annually'. However, 7 years later, according to an update paper by RAND researchers Arthur Kellermann and Spencer Jones [48], actual health expenditures in the US had risen by $800 billion. They argued that the reason why health costs rose instead of falling was that three important conditions in the original 2005 study were not met. In brief, they argued that in the US, modern IT health systems:

- were not 'interconnected and interoperable'
- were not adopted as widely as they were in Europe, although their use was growing in the US

- were not used effectively, possibly because the available systems were not easy for health care practitioners to use.

Overall, they identified the core barrier to cost reductions in the US health sector through the use of new information technology as the fee-for-service model. Their claim was that unless this model was phased out there would be little incentive for the health care industry to use data-intensive technology to reduce medical costs; it could even be used to increase them. Their findings reinforce the message learned in other sectors of the economy, that even where application of big data is appropriate, it is a necessary but not sufficient condition for promoting more sustainable—and less costly—practices. Another way in which big data might reduce costs is in the detection and prevention of fraud and abuse in medical payments [16].

Others are more cautious about the potential for big data to enhance public health, even if the problems just discussed in a US context can be overcome. Gina Neff [62] provocatively entitled her 2013 article *'Why big data won't cure us'*. Her arguments paralleled those of Kellermann and Jones, emphasising, like they did, that the use of big data (or of modern IT in general) in healthcare, still had several obstacles to overcome before it could prove its worth, including how to guarantee the privacy of the vast volumes of data collected on patients. Nevertheless, as a 2016 US report on the subject found, 'medical error is the third leading cause of death in the US' [76]. Many of these deaths would have been the result of incorrect medical diagnoses, partly caused in turn by doctors being unable to keep up with the vast literature on medical advances. Big data approaches have the potential to avoid such deadly misdiagnoses. For this and other reasons, there has been an exponential rise in health-related big data research [29].

A very different approach to healthcare was provided by Jocalyn Clark [23]. She argued that healthcare is increasingly being 'medicalised', by which term she meant that far too much emphasis is placed on short-term approaches, with their priority for medical interventions, new vaccines and drugs and new equipment (the '3Ds' of doctors, drugs, and devices). (The views of Clark are echoed in an urban health context by Christopher Dye [30], and Melanie Swan [83], discussed in Sect. 7.2.2). Clark stressed that even in recent times, 'only about 10–43% of population health is thought to be attributable to healthcare'. The rest is the result of actions taken *outside* the health sector proper, such as for income and its distribution, education and pollution control.

It follows that for big data to be most effective for urban health, it must be able to address both the problems of conventional health delivery *and* facilitate actions outside the health sector which are vital to health. A good example, discussed in Chap. 5, would be the use of big data to encourage a major shift to non-motorised modes for urban travel. Not only would the exercise provide direct health benefits, but the resulting reductions in motorised travel would lower both air and noise pollution, resulting in further health benefits through a benign circle [60]. Nevertheless, many of the proposed applications of big data in healthcare discussed below have the side benefit of reducing trips to hospitals or clinics; they therefore cut the energy use and GHG and air pollution emissions from these trips. From another angle, directly limiting air travel could help slow the spread of vector-borne and contagious diseases [86].

7.2.1 Examples of Big Data Applications in OECD Healthcare and Well-Being

We have already discussed (see Chap. 2) the growing share of older people in the global population, but particularly in the heavily urbanised countries of the OECD. For the aged, continuous monitoring of health can be important. Below is a list of possible applications of big data in healthcare that are being developed or are already being used, the first three of them for the elderly. It should be noted that these applications have usually been developed in isolation, to solve a particular health problem, such as testing for Parkinson's disease. As such, these isolated uses of big data will be less effective than would a more systematic approach to health [32]. Even so, they typically result in fewer visits needed to a clinic or physician, and so can save on both patient's time and costs. They could also improve the quality of life for the elderly by prolonging independent living.

- As an example of how embedded sensors can aid the elderly, French researchers have described a device which can detect a person falling, send this information to a monitoring station and enable the accurate location of the fallen person using a GPS system [20].
- A smart phone application (called 'Indirect Wayfinding') has been developed to help elderly people, possibly with mild dementia, find their way in unfamiliar surroundings [2]. The app allows customisation for the individual concerned and allows the caregiver to use a web portal to suggest possible destinations etc. based on the GPS location of the elderly individual. Another smartphone app called iTrem 'uses the phone's built-in accelerometer to monitor a person's body tremors for Parkinson's disease'. The app could not only lower medical costs by dispensing with costly medical tests but can also allow health professionals to assess the disability remotely [56]. In a further application of Artificial Intelligence for Parkinson's disease, University of London researchers used deep learning to enable their smartphone app to distinguish between useful and spurious data, such as that resulting from the phone being accidentally knocked. It will not only allow sufferers to do the tests at home, but pooled data will also help determine the influence of lifestyle factors on the symptoms [71], adding to our knowledge of its causes and possible means of prevention. More knowledge about the disease in general and for each patient can be gathered with fewer healthcare visits.
- As another example of how data collected for one purpose can be used for an entirely different purpose, in the UK a system ('Howz') is being tested by the National Health Service (NHS) that plugs into electricity meters [73]. Just as smart meters do, it collects information on which household appliances are being

used at any given time and for how long they are switched on. By comparing use with the average of a few days, the system can flag any change in patterns—for example, an oven being left on too long. It can then contact a designated person. Howz is presently being trialled for monitoring people who have mild dementia living with a carer. In a related example, as reported by Cook [26], one study even claimed 'to find a link between changes in mobility patterns and the onset of symptoms of dementia.' With the aid of motion sensors placed throughout the person's home, both the total daily distance covered and average walking speed could be determined. When done over several years, changes in mobility patterns were able to predict the early stages of dementia.

- Two further health apps which are being trialled in 2017 are set to be introduced in the UK in 2018 by the NHS [72]. Both will enable patients to monitor their condition at home. For pregnant women with gestational diabetes, the app allows women to measure and send their blood glucose levels to their diabetes clinician. For chronic obstructive pulmonary disease, with 1–1.5 million sufferers in the UK alone, the app allows daily measurement of heart rate and blood oxygen saturation. After 3 months of measurement, the app learns that person's normal range, and is then able to alert the relevant healthcare professional when readings fall outside the normal range. As with other medical uses of big data, both apps have reduced visits to hospitals in trials.
- In Ontario, Canada, researchers are working with hospitals to improve the treatment of premature babies [56]. 'The software captures and processes patient data in real time, tracking 16 different data streams, such as heart rate, respiration rate, blood pressure, and blood oxygen level, which together amount to 1260 data points per second.'
- Another possible use is to help the disabled—those blind, deaf or in wheelchairs—find their way in buildings, again using a smart phone [3]. The system used wireless sensor networks with cameras and sensor nodes throughout the test building to help those handicapped to navigate the building.
- In Durham County, North Carolina, data from tax returns, the census, and lead concentrations found from blood tests, were integrated. It was thus possible to prepare maps of the county showing the high-risk areas for exposure to lead and improve detection and treatment for lead-affected children. Such data integration can 'bridge the chasm that has traditionally divided population health from clinical medicine at the individual level' [98].
- Big data has potential for mental health monitoring and improvement as well. In a 2017 New Scientist article [6], the social media site Facebook was reported as planning to use pattern recognition algorithms that could indicate whether people were suicidal from their online posts. In its planned trial of the idea, Facebook will make it easier for users to contact suicide prevention help centres.
- Google in April 2017 begun a 4-year trial collecting health- and lifestyle-related data from 10,000 volunteers [7]. It is hoped that by combining disparate kinds of data—from genes to physical activity, clues can be obtained for predicting the onset of cancer and other diseases.

- We have already discussed how the smart city will ideally have a multitude of fixed sensors throughout the city to continuously measure temperature, levels of various pollutants, pollen counts, etc. People with allergies could thus be advised on the best route to travel (and the best time) to avoid adverse health reactions [81]. Similarly, joggers could be advised on the best (i.e. healthiest) route for their run. The Sense2Health application combines both features of the Quantified Self (see Sect. 7.2.2) and real-time environmental condition monitoring. Users can therefore 'track, analyze and correlate well-being states with personal exposure levels to an environmental phenomenon, e.g., noise and do so with the least active involvement possible through automatic sensing (and bio-sensing)' [40].

7.2.2 Taking Charge: The Quantified Self Movement and Online Self-Help Groups

What several of these examples show is that there is already a recognisable trend in OECD countries toward future monitoring in the home of personal health status for people with various ailments, particularly the elderly. This trend is partly driven by the need to cut health costs in an ageing society. But there is already a nascent movement of people, termed the Quantified Self (QS) movement [69, 93], whose proponents measure and monitor their personal health signs, whether they are ill or not. Deborah Lupton [54] has reported that there are now already thousands of health-related applications available for smart phones.

According to Melanie Swan [84], the QS consists of 'individuals engaged in the self-tracking of any kind of biological, physical, behavioral, or environmental information as $n = 1$ individuals or in groups.' The idea of self-tracking is not new: in the eighteenth century, Benjamin Franklin monitored both his productivity and his moral character—the later based on a list of 13 virtues [31]. Nor is self-tracking today limited to a few individuals, as today '60% of U.S. adults are currently tracking their weight, diet, or exercise routine, and 33% are monitoring other factors such as blood sugar, blood pressure, headaches, or sleep patterns [84].' While tracking one's weight on a daily basis can be simply done and generates only one data point per day, the same is not true for heart rate monitors, which take about 250 readings every second in order to assess the risk of cardiac problems. Such a sampling rate would generate about 9 gigabytes every month for each person—clearly a big data problem if used for analysis [84].

As an example of the potential benefits of personal health tracking, an article in *New Scientist* [50] has reported how the use of body sensors can even alert the user to a potential health problem—in this case from Lyme disease. If vital signs such as heart rate and skin temperature are being continuously tracked by the individual, then changes in readings may give a better indication of a health problem than comparing a one-off reading with the average of the general population, as typically happens with a visit to a doctor.

Another example comes from people who record their running distances and speeds, and share this data with other runners on social network sites. Sinan Aral and Christos Nicolaides [8] have shown how personal data sharing can motivate members of such networks to run faster and further. It is possible that sharing other personal health- and well-being-related data with other interested persons could motivate those in the network for healthier lifestyles in general.

People are taking charge and assuming more responsibility for their own health in other ways. Persons suffering from various ailments, whether physical or mental, are already using social media sites for support and information, which may itself improve health outcomes [43]. One early study [38] looked at how diabetes sufferers—who are rapidly growing in numbers worldwide [99]—interacted on Facebook. The authors found that sufferers with this chronic disease used the site for various reasons: for mutual support, for finding (and sometimes sending) out more information about their illness and its treatment, and to gain more public recognition as a community. The researchers also found that various other actors were involved in these sites: family and friends of the patients, advertisers with relevant products to sell, and the medical research community (who may be interested in recruiting subjects for research participation). All these groups may have different motivations and levels of medical knowledge, and it may prove difficult to check whether the testimonials for products advertised are fictitious or not, or indeed whether or not those posing as researchers are really marketers.

The shift to more patient empowerment, while probably inevitable if future urban health problems are to be tackled, will not be without its own problems. Both chronic disease sufferers and healthy individuals will not only be sources of data for health researchers and practitioners but will often develop their own views on management of their disease or what is needed for healthy living, including diet. Inevitably much of the information their views are based on will be variously drawn from other QS enthusiasts, from social networks for specialist diseases like diabetes, and from general online health information websites. Even a casual perusal of these sites demonstrates that the quality of this information is very variable, varying as it does from information provided by renowned hospitals to the contradictory and thus confusing advice offered by myriads of alternative health websites [94]. Reasons for the popularity of alternative medicine treatments include low levels of scientific understanding, lower cost, and avoidance of side effects from many conventional therapies. Still, such alternative treatments long predated the Internet, and in any case are used by a minority of the population, particularly for serious illnesses.

7.2.3 Discussion

Melanie Swan [83] has also sketched an optimistic view of 'Health 2050', which differs in several ways from today's conception. First, a shift from a focus on management and cure of diseases toward an emphasis on prevention and well-being, a move which is already underway. A full shift will require attitude changes in both the general public and health care personnel. Despite the problems surrounding the future of QS should it become the norm, which have been well-articulated by Bietz et al. [12], a shift to QS or similar seems inevitable if health costs are to be cut and prevention and health monitoring replace cure as the dominant health paradigm.

7.3 Big Data Applications in Non-OECD Healthcare and Well-Being

Many of the nascent applications discussed in the previous section could be applied outside the OECD, given the ever-rising share of the global population who have access to smartphones and the Internet. Nir Kshetri [51, 52] is optimistic about the help big data can provide for industrialising economies in various sectors, including health. Local entrepreneurs are already providing big data services in the more technologically sophisticated and rapidly industrialising large economies such Brazil and India, but opportunities can also be found in smaller low-income countries.

Rosemary Wyber and her colleagues [98] have reviewed both the potential risks and the benefits from applying big data in low- and middle-income country health care systems. The list of the perceived risks ('dystopian views') are similar to those that face OECD countries but could be even more severe in low-income countries. They included the usual privacy issues of poor data governance and the effectiveness and meaning of patient consent; technical problems of data integration; and perhaps most important in the short term, diversion of limited resources, both financial and human, away from more effective public health approaches. When it is considered that many of the population will be illiterate and marginalised, or from minority groups, and that standards of governance are often very low, the risks from health and other personal information being misused could be high. As with the risks, the perceived general benefits ('utopian views') are similar to the promise of big data in industrialising countries, but could even lead to a 'major and beneficial turning point in global health' [98]. Included in the list are effective privacy rules that still allow the sharing of health data, and lower costs.

Section 7.3.1 briefly discusses actual applications of big data in industrialising economies. The actual role of big data in the Ebola outbreak, and how its usefulness could have potentially been enhanced is treated in Sect. 7.3.2, along with big data's potential for detecting other disease outbreaks. A final sub-section discusses the possible future of big data in healthcare in industrialising economies, along with the supporting policies necessary if the urban public are truly to benefit.

7.3.1 Examples of Existing Big Data Applications in Non-OECD Healthcare

- In India, what could be the beginnings of an ambitious national e-health scheme is already in place. The government has begun issuing 'Aadhaar' cards with a unique 12-digit identifying number to its vast population. The planning authorities are fully aware of the potential security and privacy risks and are taking steps to avoid them [82]. The potential benefits of this scheme when implemented derive from the possibility of both generating and monitoring health data and personal data on a huge scale—and using it to greatly improve public health [98].

- A better understanding of the industrialising world's slum populations and their growth, which can aid in providing crucial infrastructure—clean water, refuse collection, sanitation—is urgently needed. In the slum areas of Nairobi, Kenya's capital city, mobile phone data was used to provide the timely data needed [51]. Conventional sample surveys would be far more expensive, and, as discussed in Sect. 3.1, their findings will often be limited value if change is rapid.
- In Nigeria, population census results are out of date and often unreliable. This created problems with distributing of polio vaccines: some settlements were given too little, others too much. With funding from the Bill and Melinda Gates Foundation, satellite images and machine learning are combined to calculate population distribution. On the basis of the data generated, researchers can identify wealthier areas from their orderly street patterns and informal settlements by their denser housing and more random street patterns. Household population surveys can then be used to determine population densities for each area type [87].
- In Botswana, a pilot program—the Malaria Surveillance & Mapping project—begun in 2011. 'Health care workers are equipped with mobile phones to gather and upload malaria-related data to the cloud' [51]. They can also provide GPS data and images to Health Ministry officials.

7.3.2 The Role of Big Data in the 2014 West African Ebola Outbreak

Another potential application is for surveillance of outbreaks for diseases such as Ebola. Ebola is a very contagious disease with a high mortality rate, but previous outbreaks were fortunately of limited extent. The 2014 outbreak mainly impacted three low-income West African countries: Guinea, Liberia and Sierra Leone. These countries have few resources for both detecting and responding to such outbreaks. For example, Sierra Leone has only two doctors per 100,000 population, compared with 245 in the US [4]. Milinovich et al. [58] have argued that digital surveillance could improve response to outbreaks of this disease, as even in the low-income countries of west Africa, ownership of mobile phones is high and growing.

Fung and colleagues [37] have also pointed out another use made with big data approaches to dealing with Ebola disease. The US Centers for Disease Control (CDC) developed a model which can map projections of Ebola cases, with and without public health intervention. These easily understood maps proved a powerful means of *communicating* to relevant policy makers of the seriousness of the outbreaks and the consequences of inaction.

Twitter traffic, on-line news stories, and Internet searches about the disease could help pinpoint outbreaks in the early stages. Although this method may not be perfect, it may prove invaluable in low-income regions where more conventional disease surveillance methods are not well developed. Such use of social media and news feeds has already proved its worth for public health elsewhere. In 2002, the emergence of Sudden Acute Respiratory Syndrome (SARS) was first detected by a Canadian health news aggregator service.

7.3.3 Discussion

Many low-income countries lack both the necessary laboratory equipment and trained personnel, so getting tests analysed can be time-consuming. Smart phones potentially offer a way around this problem, and many of the health applications being developed could have even more relevance for such countries than they do for OECD countries, particularly as cellular networks there tend to be more reliable than both the electricity supply and even the availability of clean water. The apps being developed include one to detect schistosomiasis, a debilitating disease caused by parasitic infection. The test uses a mobile phone attachment to identify the presence of the parasites' eggs in urine and stool samples. Another app is a simple test for river blindness, another parasitic infection prevalent in Africa [66]. Such easily-obtained health care data could empower local people, and form the basis for surveillance for disease outbreaks.

Discussion of lifestyle changes—getting more exercise, eating healthier food and so on—is simply irrelevant for many residents of low-income cities, especially the hundreds of millions living in slums. They may have little choice in their lifestyle; they may not be able to avoid either drinking unsafe water or living in insanitary conditions. Unless these basic human needs are met, big data health applications can only be limited value in improving slum residents' health, even assuming the relevant technical expertise and infrastructure was available to health officials. Of course, better knowledge of, for example, the dynamics of informal settlements and the many problems facing their residents, could be helpful: the surveys of the poor in London and other cities by Seebohm Rowntree and others at the turn of the twentieth century were essential for improving their condition [96]. Even so, governments must be able and willing to provide the necessary resources to overcome these problems.

Nevertheless, governments in low-income countries do not necessarily have to rely solely on their own financial resources and technical expertise. In the case of Ebola, the risks were so great that international aid and expertise (from the WHO and especially Médecins Sans Frontières) complemented efforts by local health officials. More accurate and more detailed population estimates for settlements in Africa—and in fact anywhere in the world—benefitted from decades of high-resolution satellite images. Especially in the latter case, there are few problems with privacy.

7.4 Case Study: Instrumented Chair for Health and Comfort[1]

7.4.1 Introduction

An example of the Quantified Self is given here: the instrumented chair (the 'Virtual Spine' system) developed by the first author (in collaboration with Applied Health and IT researchers at Monash University Australia) to improve sitting posture and avoid back pain [90–92]. The application, like QS itself, is presently more relevant to OECD countries.

Sitting is one of the most common behaviors in people's daily life. A recent epidemiological study on about 50,000 adults from 20 countries reported sitting time was 300 min/day on average [11]. Incorrect sedentary positions and prolonged sitting has become a serious health threat to people in modern societies and results in various spinal problems [95]. A large number of studies have convincingly reported the association between different levels of exposure to occupational sitting and the presence or severity of low back pain (LBP) [74]. There is also unequivocal evidence that sitting and upper quadrant musculoskeletal pain are related [17]. The third European Working Conditions Survey identified the most common work-related health problem as back ache, reported by 33% of respondents [65]. These problems often result in absence from work or even permanent disability and translate into high economic costs [88].

It is a challenge for people to maintain appropriate sitting positions in daily life to avoid seating-related health issues. In the literature, discomfort and pressure sores have received particular attention in military [25], workplace [41] assisted living [59, 78] and mobility [1, 15, 80] contexts. For instance, the findings from Caneiro et al. [21] have demonstrated a clear link between thoraco-lumbar postures while sitting, and head/neck posture and motor activity. Burnett et al. [18] articulated the challenge to maintain appropriate sedentary behavior to reduce extra the burden to the spine and trunk muscles.

What is good posture? According to Claus et al. [24]: 'Good posture may be influenced by demands to prevent movement, coordinate movement, safely load spinal segments or conserve energy.' Despite the controversy around what constitutes an ideal sitting posture [64], it is clear that fixed postures, particularly in prolonged sitting, constitute a high-risk factor for developing LBP due to the static loading of soft tissues and discomfort [67]. As a preventive strategy, fixed postures in prolonged sitting should be avoided. Therefore, monitoring the spinal movements to prompt appropriate proactive measures is urgently needed.

Motivated by these findings, researchers from different disciplines are working on automatic monitoring of sitting postures to promote healthy sitting behavior. Specifically, clinicians are increasingly adopting spinal motion analysis as a useful

[1] This section is a slightly revised version of sections I–III of Wang and Yu (2013), Ref [92]. Used by permission of IEEE.

clinical method to quantify the range of trunk motion and pattern of posture changes for diagnosis and outcome evaluation. For example, skin surface tracking (from markers/sensors adhering to the skin overlying spinous processes) has been used to quantify spinal curve and the change in the lumbar spinal curve between positions from flexion to extension to identify optimized sitting posture [24]. Haller et al. [42] equipped an ergonomic office chair with four sensors to measure an office worker's posture and to produce different alerts to help people improving their sitting posture. However, the possibility of using a Pervasive Environment Simulator (PES) to collect and present through interactive 3D display detailed postural information has not been previously investigated.

Today, with the development of intelligent embedded agents and pervasive computing environments, performing experiments in a PES based game engine environment has become a cost-effective method to simulate users' real-time behavior [28]. The ideal model of a PES user monitoring and advisory system would comprise four seamlessly integrated modules:

- multiple sensors
- comprehensive data analysis (agents)
- interactive 3D (Mixed Reality)
- messaging.

Such a system enables multiple users to simultaneously view, discuss, and interact with the virtual 3D models, and enhance practice by supporting remote and co-located activities [13]. The multiple sensors module monitors various data about the users. A comprehensive agent model is designed to constantly monitor users' everyday activities [19]. Interactive 3D (Augmented Reality or MR [10]) displays provides great flexibility of viewpoint and intuitive interfaces to present information and support users to change their behavior [34]. Such a messaging system may act as powerful persuader because it can intervene in the right context as a convenient way to prompt users to change their behavior [14, 33, 100].

Ubiquitous computing and context-aware persuasive technologies [33] offer an opportunity to promote healthy behavior by presenting 'just-in-time', 'appropriate time' and 'appropriate place' information [45, 46]. An interesting discovery from this research is that the appropriate sedentary position varies depending on the *purposes* for which people sit: for example sitting in the office, in the car, or when dining, etc. The main focus of the Virtual Spine system design is to:

- monitor people's sedentary behaviour across various circumstances and encourage people to maintain appropriate sedentary positions under various contexts
- provide location-aware advice, for which the system relies on the 'chair id' to reflect the surrounding environment
- provide advice at the right moment, for which the system requires knowledge of the users' activities.

Advice on correct sedentary posture must fit easily into users' daily routine since messages suggesting simple activities are preferred over ones requiring significant effort [55]. Besides, lifestyle interventions can yield positive and long-term effects, in terms of increasing levels of moderately intense physical activity [36]. The suggested locations of lifestyle activities we include in our system are [36]: everyday activity (shops, homes, schools, workplaces, etc.) and recreation destinations (playgrounds, parks and gardens, etc.) Based on the current research and technical capabilities outlined above, in the next sections, we present a 'Virtual-spine' system that provides users with personalized and contextualized advice on appropriate sitting positions. We introduce the design, implementation and a planned evaluation test of the Virtual-spine system.

7.4.2 Implementation of the Virtual Spine

The Virtual-spine is implemented using the Unity3D and Arduino platforms. The Unity3D engine supports exporting application to mobile platforms, which will render the 3D images in real-time, based on the data from the Sedentary Position Analysis Unit.

The Virtual Spine consists of the following components:

- Sedentary Sensory Unit
- Advisory Unit
- Interactive 3D Unit
- Messaging Unit

Sedentary Sensory Unit

The Sedentary-Sensory Unit is designed to monitor users' spine movements while sitting by detecting the center of gravity and back curvature. This unit can be designed in suitable forms, such as pad-like shape, and set up in various places to gather sedentary position information in different contexts like at the office, at home or driving. Each unit has a unique ID used to recognize which chair the user is sitting on. This information is sent to the Advisory Unit which processes it to compute the cumulative spinal burden. Comprehensive sedentary information is presented to the user on mobile devices, computer screens or smart TVs as real-time rendered interactive 3D images. To reduce the burden on the spine, and to motivate users to maintain healthy sedentary habits, messages are presented pervasively using the most appropriate media. For instance, advice will be displayed on TV when the user is sitting on the sofa, or on a mobile device if the user is sitting on an office chair. Presentation settings could be tailored to users' privacy and other needs. The system architecture is illustrated in Fig. 7.1.

The Sedentary Sensory Unit provides high-sensitivity 'Pressure Sensing', 'Chair-ID Recognition' and 'Profile' functions. When users sit or even semi-sit on the sensing pad, their body affects the pressure sensors on it. Each sensor sends the detected values as analog input, which affects the 3D visualization through the Advisory Unit. Multiple physical pads should be placed on the seats habitually used for the different purposes. The pads' IDs determine the use context of each seat to provide correct posture parameters to the Sedentary Position Analysis unit. If the

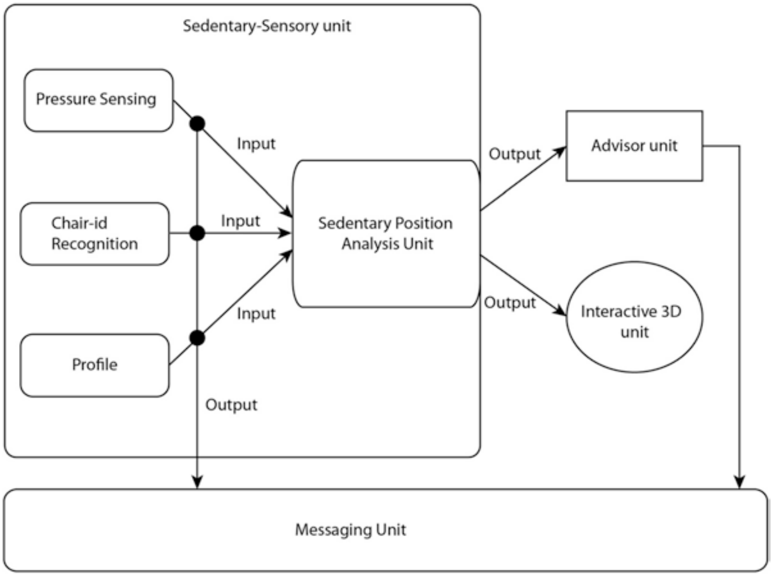

Fig. 7.1 System architecture for Virtual Spine

incorrect sedentary posture lasts over a set time threshold, the Advisor Service sends a message to the mobile UI.

1. *Pressure Sensing.* We used Force-Sensitive Resistor (FSR) sensors and an Arduino platform to detect postural changes. Sensors are laid out using a 'near-optimal sensor placement strategy' [61]. Any curvature variation of the body trunk is converted to analog input that affects the virtual 3D spine in real-time. The connection between Arduino and Unity3D is provided by a 'unity-Arduino serial connection' [68]. Figure 7.2 shows the Sedentary Sensory Unit (left), sensors affecting the virtual mat (middle), and interactive 3D spine (right).
2. *Chair ID Recognition*. Functionality and ergonomic characteristics such as seat height, depth, back support angle, surface material, flexibility (adjustment), etc. for each chair are stored in a database with a unique ID. The 'chair-ID' is recognized when users sit and *then* combined with users' profiles to calculate the most appropriate postures and sitting periods. The Chair-ID recognition function is based on Internet of Things technology. Currently, there are only a few companies providing free services to store IDs, profiles and input/output data in real-time (pachube.com, open.sen.se, etc.) Chair specifications could either be directly input or acquired from the manufacturers' database. The latter option also creates opportunities to design future 'smart' chairs, which could monitor ergonomic adjustments and send them to the manufacturers' database to inform design refinements. Users fill in their profiles through the online interface, providing information such as body size, gender, age, common sitting time, type of transportation, etc.

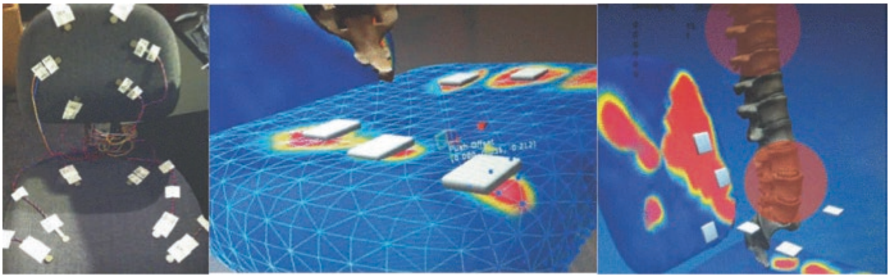

Fig. 7.2 Sedentary sensory unit

3. *Sedentary Position Analysis Unit.* Unhealthy postures are recognized based on duration and detected deviations from the ideal spinal position. Claus et al. [24] have suggested that the 'ideal' sitting position depends on the angles of three divided spine sections: 'thoracic, thoraco-lumbar and lumbar'. The posture detection system uses a comparison algorithm to analyze the spinal positions of each section. The chair-seat sensors are divided into four sections: a (left-front), b (left-back), c (right-front) and d (right-back) to work out the position of the lumbar area. The chair-back is divided into two sections: e (left) and f (right) to calculate the position of the thoracic area. The Analysis Unit compares the pressure input from these sections to calculate the thoraco-lumbar spine section position and movement. For instance, if the value of 'a' is much greater than 'b', 'c' and 'd' and both 'e' and 'f' are 0, then the user is heavily leaning to the left-front direction. However, if the values of 'e' and 'f' are also large at the same time, then the user is in a left leaning 'sloppy' position, as the thoracic area is positioned backwards.

Advisor Unit

Based on the posture recognition, chair-ID, and profile, the Advisor Unit calculates a suitability score for each advice in the activity database. Advice is generated through an expert system that considers the following factors:

- Spine angle: sharp angles cause extremely heavy burden on the spine and should not be maintained for a prolonged time
- Prolonged time: this parameter measures the duration of a position
- Accumulated sitting time: cumulative sitting time on different chairs to calculate total sitting time
- Frequency: how often the user takes the same position.

Instead of monitoring how the user follows the suggested activities, this system follows a decide-choose-do format to accumulate the chosen activities into the database. The Advisor Unit sends a query to one or more of the services and acquires their analysis results. If all the factors are met, the advice becomes a candidate. The advice mainly contains several types of message:

- Warning: to alert the user that it is time to change posture and stop sitting
- Activity: to suggest users take a proactive relaxation approach and what kind of activity is appropriate for their context. This type of message normally gives user several options to choose from depending on the contextual restrictions and time limitations
- Relaxation: to give the option to rest rather than doing exercises; this type of message suggests a minimum time-span during which any sitting should be avoided.

Here we present a sample scenario to show how it might work. Mr. A has been continuously working in his office chair for more than 3 h, and only maintained a healthy posture for less than 20% of this period. He will receive the following message: 'Please stand up straight with your arms at your sides, bend sideways to the left, slide your left hand down your thigh and reach with your right arm over your head. Hold this position for 10 s, then return to the starting position and repeat for the opposite side. Alternate sides for nine more times'.

Interactive 3D Unit

The 3D display unit presents spine information in two modes: a 'real-time mode' and an 'accumulation mode'. The real-time mode presents the user's current spinal position and corresponding burden. The accumulation mode presents the cumulative spinal burden information gathered during a certain period. Advice is mainly generated based on the accumulation mode data. It is very rare that a warning advice is directly generated from the real-time mode as this only happens when a user's movement results in an extreme burden to the spine.

Messaging Unit

Unlike conventional location-based pervasive functions, the Messaging Unit application uses the chair ID to recognise users' locations. This unit interacts with users by sending messages generated by the Advisory unit through the most appropriate medium.

7.4.3 Discussion

In the Virtual Spine lab unit, new techniques and materials are required to enable specifically purposed health monitoring, in this case, to improve spinal alignment by placing 'e-Skin' sensors on the spine area to monitor the key inter-vertebral disc

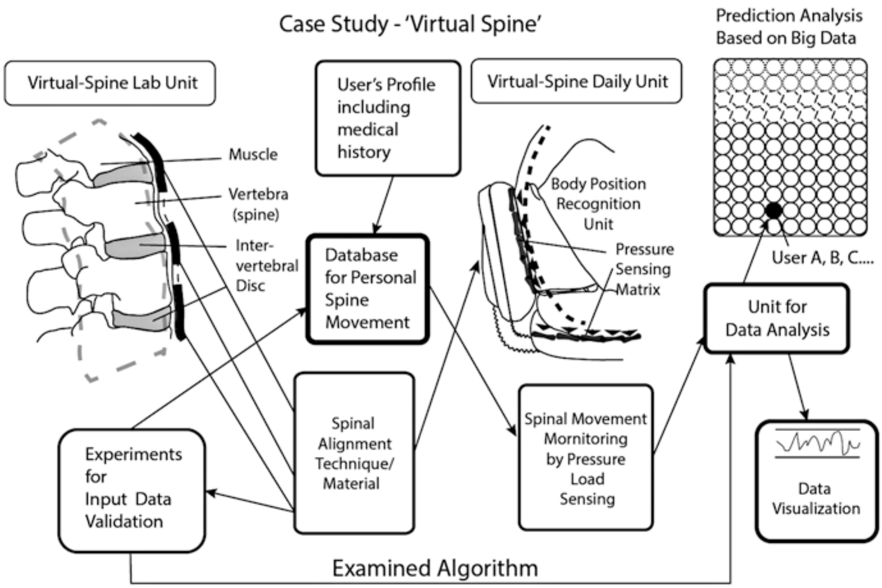

Fig. 7.3 The Virtual Spine platform as a case study for big data personal health support

expansions. The monitoring method will need to be validated through examining data examining data gathered from a series of tailored experiments. A database will then be built to store the samples of personal spine movement; this step is necessary to test, review and construct the appropriate database architecture. To provide personalized health support, a user's profile also needs to be built. The profile information will be used together with the spine movement data; both need to be contained in the database.

The Virtual Spine Daily Unit will need to be well designed, practical and attractive enough to be sold to various users to be part of people's daily life. The unit will be equipped with a pressure load sensing unit to enable spinal movement monitoring. This daily output data will be raw data which won't make any sense to users. However, based on the needs of users (e.g. medical practitioners and patients) some valuable/useful information (or knowledge) can be processed out with the unique algorithm from the outcomes from the validation experiments; this process will be achieved by the data analysis unit. According to various needs, the analyzed data can be visualised differently through a data visualisation unit.

The data, when analysed for all users, will be a big data set which could contribute to information on spine movement, spine health, sitting behavior, working habits, working condition for white-collar workers and so on. Figure 7.3 summarises how the data would be collected, and analysed.

7.5 Discussion: The Potential Benefits and Risks of Health Big Data

The use of big data for public health promises to bring many benefits but also carries some risks. As Vayena et al. [89] have pointed out, some of these downsides are present in public health regardless of the techniques used, while others are unique to big data approaches.

One possible danger with the potential for one version of personalised treatment promised by success in mapping the human genome is that notion of *public* health will be downgraded, and only the well-off will be able to afford medical care [97]. This is not only an equity problem. In most cities of the industrialising countries, contagious diseases are still a major cause of mortality, and ongoing climate change could increase the risk from these diseases. In the case of disease outbreaks like cholera or Ebola, the health of others affects the health of each individual.

Nevertheless, there is great potential for big data to improve health for all, both in the OECD and other countries, as illustrated in Sects. 7.2.1, 7.3.1 and 7.3.2. The QS movement—where people take more responsibility for their health—is a welcome development. The case study on the Virtual Spine, discussed in detail above, is an example of QS, and also suggests how the measurements for different individuals could be pooled to advance our knowledge.

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