What Does Big Data Mean for Wearable Sensor Systems?

Contribution of the IMIA Wearable Sensors in Healthcare WG

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Summary

Objectives: The aim of this paper is to discuss how recent developments in the field of big data may potentially impact the future use of wearable sensor systems in healthcare.
Methods: The article draws on the scientific literature to support the opinions presented by the IMIA Wearable Sensors in Healthcare Working Group.
Results: The following is discussed: the potential for wearable sensors to generate big data; how complementary technologies, such as a smartphone, will augment the concept of a wearable sensor and alter the nature of the monitoring data created; how standards would enable sharing of data and advance scientific progress. Importantly, attention is drawn to statistical inference problems for which big datasets provide little assistance, or may hinder the identification of a useful solution. Finally, a discussion is presented on risks to privacy and possible negative consequences arising from intensive wearable sensor monitoring.
Conclusions: Wearable sensors systems have the potential to generate datasets which are currently beyond our capabilities to easily organize and interpret. In order to successfully utilize wearable sensor data to infer wellbeing, and enable proactive health management, standards and ontologies must be developed which allow for data to be shared between research groups and between commercial systems, promoting the integration of these data into health information systems. However, policy and regulation will be required to ensure that the detailed nature of wearable sensor data is not misused to invade privacies or prejudice against individuals.

Keywords

Big data, wearable sensors, ambulatory monitoring, standards, privacy

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1 Introduction

1.1 The Rise of Wearable Sensors

A wearable sensor is a small electronic device containing one or more sensors which can transduce information which is related to the device user, the ambient environment, or the users' interaction with the environment (as may be facilitated by RFID tags embedded in domestic appliances, for example). Common sensors used in such wearable monitoring systems include those for measuring movement and position [1], such as accelerometers, gyroscopes, magnetometers, barometric pressure sensors, and GPS, or sensors for assessing electrophysiological and chemophysiological function, or other physiological properties such as body temperature.

One of the oldest and most prolific wearable sensors is the Holter electrocardiogram (ECG) monitor, which has been in clinical use since the 1960s [2)]. The Holter monitor performs 24-hour ambulatory ECG recording for the purposes of capturing intermittent cardiac arrhythmias, which might otherwise be missed using standard assessment practices. The use of this technology in ambulatory clinical applications was made feasible by the invention of the solid state transistor, which facilitated the miniaturization of the bioamplifiers used to capture the ECG potentials, reducing the size of the apparatus from its initial weight of approximately 40 kg to a device similar in size to a smartphone [3].

For the Holter monitor, as for other wearable sensors which will be discussed hereafter, recent advances in memory capacity and miniaturization, low-power and high-speed microcontroller design, and battery technology, have enabled the manufacture of devices which are smaller in size, can record more data, and last longer than ever before. In addition, the recent proliferation of wireless communication technologies and continued improvements in global communications infrastructure have resulted in the ability to wirelessly retrieve wearable sensor data, in real-time, from almost anywhere in the world.

However, while the aforementioned technological advancements have made the general widespread use of wearable sensor systems a more feasible and practicable prospect, the most exciting developments in wearable sensor technologies have been driven by progress in the design of the sensors themselves, and specifically by advances in microelectromechanical systems (MEMS). For example, state-of-the-art off-the-shelf MEMS devices can house a triaxial accelerometer, triaxial gyroscope, and triaxial magnetometer in a low-power electronics package measuring only several millimeters along each dimension. Similarly, it is possible to measure barometric air pressure and ambient temperature with a MEMS device of comparable dimensions. While GPS modules are small enough to be housed within wearable sensors, and are now commonly found in smartphones, their size is considerably larger than the MEMS devices mentioned above, but still small enough to fit inside a typically wearable sensor case. Progress has also been made in the design of wearable sensing technologies for recording clinical measurements; for example, ECG biopotentials and respiratory movements, using flexible electronics mounted on wearable patches.

Ultimately, the availability of such miniaturized sensors which can continuously measure global position, altitude, movement, and physiological function, will have profound implications for how health and wellbeing are assessed and managed in the future.

1.2 Aims

This paper will present the opinions of the IMIA Wearable Sensors in Healthcare Working Group on the perceived advantages and disadvantages which are likely to arise from the widespread adoption of wearable sensor systems in the future. In particular, a discussion is presented on how wearable sensor systems will generate data streams with significant heterogeneity, sporadicity and volume that transmission, storage, organization, interrogation, and most importantly understanding these data would be considered to fall within the class of data analysis problems encompassed by the fashionable term *big data*. Some outstanding and anticipated technical and social challenges facing the discipline are introduced, within the context of big data, and in some cases suggested solutions to these problems are put forward, with the hope of guiding future research and development (and possibly governmental policy) in this area.

Before proceeding to discuss the big data challenges facing the future development of wearable sensors systems, the following section provides a brief overview of some wearable sensor applications, with the intention of providing the reader with some understanding of the nature of health applications for which wearable sensor systems are considered useful, ultimately adding context to the big data discussion which will follow.

2 Applications of Wearable Sensors

Ludwig *et al.* identify six categories of services provided by health-enabling technologies [4], which are listed as follows: (A) Handling adverse conditions; (B) Assessing state of health; (C) Consultation and education; (D) Motivation and feedback; (E) Service ordering; and (F) Social inclusion. One might suggest that wearable sensor systems are most strongly associated with service categories (A) and (B).

2.1 Applications in Reactive Healthcare – Handling Adverse Conditions

Ludwig *et al.* subdivide category (A) into: (A.1) Manual emergency call; (A.2) Automated detection of deviant behavior; (A.3) Automated detection of falls; (A.4) Automated detection of cardiac emergencies; (A.5) Handling potentially dangerous situations.

Subcategory (A.1) represents one of the most successful and widely-used wearable sensor applications. The most common embodiment of this sensor is a small plastic waterproof (or water resistant) device worn on a lanyard around the neck. If the user is concerned for their wellbeing, they can press a large button on the front of the device to summon help. Pushing the button sends a radio signal to a base station phone within the home, which places a call over the public switched telephone network to a human operator at a remote monitoring call center who coordinates the response. A number of commercial systems are currently offered globally by various service providers, including Tunstall (UK), Grupo Neat (Spain), Philips (Netherlands) and VitalCall (Australia), and require an upfront installation fee and an ongoing subscription fee.

However, there is a risk that the user will not have capacity to press the button if they are distressed or injured. For example, fall incident rates for those users with dementia is more than twice that of normal people of a similar age, but these dementia sufferers are less likely to have the presence of mind to activate the panic alarm when they fall [5].

Compliance and usability issues like this promote the need for automated algorithms to detect adverse situations, without the need for users to initiate the request for help. Ludwig *et al.*'s subcategories (A.2-A.5) all entail the automated detection of some such adverse situations, like a fall, a cardiac event, or some other dangerous situation (such as a dementia sufferer wandering away from home). The scientific literature contains many reported algorithms which aim to automate the detection of falls in the home, primarily using accelerometry-based wearable sensors; see Shany *et al.* [1] and Schwickert *et al.* [6] for a review on fall detection algorithms. However, due to the relative rarity of fall events (approximately one in three people over 65 years will fall each year) there have been very few reports of the testing of these algorithms on data from real-world fall events; Bagalà *et al.* provide one of the very few reports of algorithmic performance on real-world falls, although these fallers were suffering a form of Parkinson's disease, hence it is unclear how generalizable these results are [7]. This issue of proving efficacy of algorithms intended to predict rare events will be revisited later in the paper; this is a major challenge for scientific researchers and a problem from which big data provides little respite.

2.2 Applications in Proactive Healthcare – Assessing State of Health

Category (A) above describes monitoring which results in a reactive response to an acute adverse situation which has already occurred. The application of wearable sensors described by Ludwig *et al.*'s category (B) has recently been attracting much attention from researchers. The authors subdivide this category to include: (B.1) Recognition of unknown diseases and medical conditions;

(B.2) Monitoring known diseases; and (B.3) Monitoring of therapeutic interventions [8]. It could also be proposed here that these definitions be broadened to include prediction, or risk assessment for future health conditions or events, such as falls [9, 10].

Using wearable sensors to monitor cardiovascular function, physical mobility, and activity levels, or the specific nature of daily activities in which the user engages, it is envisaged that wellbeing may be more proactively managed, allowing targeted interventions to be administered at an earlier stage [1]. The high frequency with which health-related assessments may be obtained using wearable sensors (which may even deliver continuous signals) is expected to enable closed-loop control of health conditions, whereby the outcome associated with a medical intervention or change in lifestyle is immediately evident and measurable with wearable sensors, ultimately improving the standard of care achievable. Moreover these monitoring approaches could be applied for rehabilitation purposes, for example, in cardiac rehabilitation in a post-acute care scenario, or subsequently for lifestyle monitoring and promoting self-care.

3 Big Data Challenges for Wearable Sensor Systems

3.1 Wearable Sensors Can Generate Big Data

Big data is a term describing datasets which are large, fast-growing, heterogeneous, and contain substantial amounts of noise. The term big data may also encompass the new analysis methods and technologies required to store and understand big datasets [11]. It has been suggested that four Vs, *volume*, *velocity*, *variety*, and *veracity,* should be used to describe these qualities of a big dataset [12]; here volume relates to the complexity of the dataset, rather than the memory capacity required to store the dataset, although there is an expectation that both would often be correlated. Obviously, the classification of a dataset as being big data is a relative notion which is determined by the current state-of-the-art in data hosting and analysis techniques. A fifth V, *value*, is also often ascribed to big data, describing the commercial potential data mining such large datasets can provide.

Over the past half-decade the potential scientific and societal advantages of big data utilization have been explored, which are partly summarized in reviews in Science [13] and Nature [14].

Wearable sensors have the potential to generate big datasets. Considering a wearable inertial sensor which measures triaxial accelerometry, gyroscopy and magnetometry at 100 Hz, and barometric pressure at 2 Hz, and assuming two bytes per sample per signal, this will generate approximately 156 MB of data per day. Battery power is perhaps the most substantial factor limiting the volume of data generated by wearable sensor systems. There is a trade-off between transmitting all data to a server and preserving battery life. Preprocessing data on the sensor to extract salient information before transmission will preserve battery life, since the amount of data transmitted (and hence the duration for which the radio is active) is reduced; however, this implies that information is discarded in the process. If battery life, low-power circuit and sensor design, and budding power scavenging technologies are all improved upon in the future, even more data will become available from wearable sensors. It should be noted that it is still feasible to wirelessly retrieve all data if devices are charged daily, but having to recharge frequently may reduce acceptance.

With regards to the complexity (which is really what is meant by the term volume) of the data generated in the above example, these sensor signals encode aspects of human movement, but simultaneously, and at a higher level of abstraction, the users' physical strength and mobility, engagement with their environment, and ultimately complex aspects of their physical and mental wellbeing. The inertial signals used in this example are each very different in nature, and the inclusion of other sensing modalities, such as GPS, audio, camera, or ECG, further diversify sample rates and data characteristics. In addition, data may not necessarily be acquired continuously, but rather (depending on demand) sporadically or with non-uniform sample rates (due to battery limitations mentioned above), adding to the heterogeneity and variety of the data.

It was stated above that wearable sensors will generate data which satisfy the first three Vs of big data: volume, velocity and variety. The fourth V of veracity is also relevant to wearable sensor data. There are numerous examples of situations during unsupervised monitoring using wearable sensors when raw signal data can be corrupted. Some notable mentions involve poor device affixation or failure to wear the sensor when recording inertial signals [15], and electrode movement or detachment during ECG recording [16]. Verifying the quality of data acquired during unsupervised monitoring is currently an active research area which employs both hardware and algorithmic solutions to ensure that poor quality data is identified and rejected [17-19]. It remains to be seen whether the complex relationships and context present in big data sets will allow the negative impact of these noise artifacts to be further mitigated.

3.2 Data Formats, Communication, Storage and Management

Wearable sensor technologies are still at a nascent point along a trajectory that other health monitoring technologies have already traversed. One of the next steps along this path will require the harmonization or standardization of data formats towards a preferred open data format and the inclusion of appropriate metadata to provide necessary context regarding the data acquisition and initial analysis. Many current systems use proprietary data formats, rather than adopting an established open standard, like Hierarchical Data Format 5 (HDF5), for example [20].

However, a more problematic issue relates to the nature of the unprocessed or raw data, which is directly generated by various wearable sensors. Two devices containing the same sensor set may offer up very different data which it will claim to be raw data. A common example of this has arisen in the past for activity monitors. Some older activity monitors (e.g., Stayhealthy RT3) generate a proprietary measure called an *ac-*

tivity count, which is estimated every minute; this value counts how often the acceleration magnitude exceeded some preset threshold in one minute. Difficulties arise when trying to compare outputs of various sensors if their respective manufacturers use different activity thresholds, signal processing algorithms, sample rates, or filter settings.

The naïve solution may suggest that all devices should record and transmit raw signal data at a standardized sample rate, without any onboard preprocessing; however, this is currently not a universally practicable solution, mainly because battery restrictions for some applications necessitate preprocessing data on the device for data compression and extraction of salient information in order to reduce transmission rates and preserve battery life. Also, different applications inherently require different sample rates due to the nature of what is being monitored. If standards are to mandate sample rates and filter settings, these should perhaps be application specific.

At a higher level, wearable sensor data (and biomedical signal data in general) would benefit from an overarching architecture similar to that of Digital Imaging and Communications in Medicine (DICOM), which standardizes how medical images and associated properties (such as patient identifiers) can be stored as a digital object and communicated over a network [21]. In addition to acquired sensor readings, an equivalent standard for wearable sensor data might encode sensor types, manufacturers, models, and other properties which may be reprogrammable, such as sample rate, sensitivity and dynamic range, as well as other external information, such as device placement location and orientation on the body (if known). Some researchers have initiated this standardization; for example, see Klenk *et al.* [22] and the EU Framework 7 FARSEEING project. However, these standards tend to be steered by the need to advance a specific research area, such as enabling data aggregation across fall detection research studies in the case of Klenk *et al.*, hence their standard also makes accommodations for the collection of ancillary gold standard data regarding fall events, against which future automated fall detection algorithms will be evaluated.

The major limitation with many data encoding schemes for wearable sensors is that researchers and industry use their own (often proprietary) concepts and terms to annotate and give meaning to data (metadata). Unless a storage format has been designed specifically to capture and hold this metadata, then this information will commonly be stored separately to the actual data or may be lost or misinterpreted when data are converted or exchanged. One recent initiative, with its genesis in the VPH-Physiome project [23], proposes a BioSignalML markup language to allow flexibility and extensibility of data and metadata representation and storage for biosignals [24]. Crucial to the BioSignalML initiative is that there is no intent to specify another storage format. Rather, open data and metadata standards, namely those from the Semantic Web, are used to describe signals in their existing formats. Thus the BioSignalML ontology provides a universal framework, allowing biosignals to be represented, unified, extended and linked with other resources on the Web.

Formalizing how wearable sensor datasets are stored and communicated will allow the pooling of datasets from multiple locations around the globe. This achievement will increase the purity of this data, by minimizing the confounding effects mentioned above relating to variations in sensor types and settings. While the technical and logistical issues associated with developing standards for wearable sensor data are great, they would certainly be considered surmountable. By far, the greater challenge is to organize and discover useful information within these big data.

3.3 Analyzing Data

Interpreting big data from wearable sensors will face many similar challenges that other big datasets pose, and perhaps more.

Firstly, the data is heterogeneous, originating from different sensing modalities. Indeed, these data need not only originate from wearable sensors; using wearable sensor to complement other health data in order to improve clinical decision making is likely to be a major incentive for their use, and the aggregation of wearable sensor data and more traditional health data will increase the complexity and heterogeneity of the overall dataset.

Another challenge arises from the potentially sporadic nature of the data. Signal processing methods for dealing with nonuniformly sampled data, specifically data containing large temporal gaps, is not well developed when compared to the methods available for uniformly sampled data; even filtering or smoothing nonuniformly sampled longitudinal data to remove noise is not a trivial exercise, and interpolation and resampling can lead to false confidence in parameter values where long periods of data are missing; for example, see locally weighted scatterplot smoothing [25].

Clearly, wearable sensors provide the capability to monitor more frequently than would currently be achievable, say, by visiting the general practitioner (primary care physician), for example. Therefore, this temporal resolution is definitely seen as an advantage of continuous monitoring with wearable sensors, as it is unlikely that adverse health events will be missed (for example, nocturnal cardiac arrhythmias). This continuous monitoring is obviously valuable in scenarios where it is known exactly what the observed pattern indicative of failing health is (for example, an easily recognized ECG containing an arrhythmia); but then that advantage does not need to make any use of the capabilities of big data, but rather simply requires frequent or continuous monitoring. The large volumes and complexities of big data promise to enable the discovery of new relationships, and to do so with high statistical confidence. Given that we must mine through big data to discover new relationships, in certain instances the additional data generated by continuous and multimodal recording can actually make it more difficult to discover the desired relationships between sensor readings and health status.

There does not appear to be a good consensus on how best to interpret the resulting multiparameter longitudinal records generated by wearable sensor systems [8]. When it comes to automatically labeling a vector of features values indicative of health status into a category of wellbeing, statistical pattern classification models are mature enough to perform this task well. What is often poorly understood, or simply unknown, is what are the best features which can be extracted from the available sensor (or other ancillary health) data in order to make this determination of wellbeing; this is particularly difficult for wearable sensor data, as it is both multidimensional and temporal in structure. Modelling the underlying mechanisms which give rise to the observed feature values would enable a reduction in the complexity of the dataset, and the model parameters may in turn be used to infer the state of wellbeing of the individual. However, due to the highly complex nature of big data and the potential disparity between data sources, developing a model which would explain the observed sensor values, and hence reduce the complexity of the dataset, is an endeavor likely to enjoy only limited success. In such complex scenarios, the last resort is to mine through the dataset in the hope of finding a relationship between the observed variables and some gold standard measure of health status. There are, however, some serious caveats which should be heeded when this approach is employed.

Successful mining of any dataset, big or otherwise, is dependent on the ratio of the number of available training examples to the number of features extracted. The number of potential features which could be extracted from any dataset is infinite, so common sense and domain knowledge is often used here to guide these choices; although for complex or novel data sets, little domain knowledge may be available to steer feature design. Particularly for predictive or prognostic models, many have erred in the past by overlearning on small training sets, generating models which perform poorly when applied to an independent data set or when deployed in the wild [26, 27]. It is tempting to believe that collecting yet more sensor data will mitigate this risk of overlearning, as we have more information about the problem, but this would be a false assumption. It is most important to maximize the number of training examples available.

Unfortunately, for many (but not all) medical research problems, acquiring training examples for models, be they predictive models, risk models, or decision support models, is a demanding task. The prohibitive cost and technical challenges associated with running trials of wearable sensor systems often limits cohort sizes to the several hundred participants. Given that it is often fledgling technology companies who are innovating in the wearable sensor (and home telehealth) space, developing and validating algorithmic tools to interpret complex sensor and medical record data in the face of strict regulatory approval criteria burden these pioneers with a cost and risk that cannot be sustained given the revenues and financial support available to the typical start-up company.

If the event which would constitute a positive training example is also a rare event, such as an older person falling (given that one in three people over 65 years falls in a year), then the cohort size and monitoring time must both be increased to capture a sufficient number of events to obtain statistical significance and power. This slow rate at which gold standard measures of wellbeing can be acquired is the bottleneck which will impede the full promise of big data use for healthcare from being realized, for certain applications.

The solution to the challenge of small dataset size in medical research requires a consolidated global effort. Data should be aggregated on a global scale and made publically available using an agreed format for data and knowledge interchange, as discussed previously; these sentiments have also been echoed in a 2009 editorial publication in Nature [28]. The PhysioNet database is an example of one such repository of publically available biosignals [29]; although data hosted here is publically available, data from different studies are not often comparable in structure. Hence, trial protocols should be standardized as per the example listed earlier for the FARSEEING project. Data sharing on this scale will also average out experimental bias between research groups and avoid the urge to overfit small datasets.

3.4 Acceptance of Wearable Sensors and Ubiquitous Monitoring

The discussion above has focused on the challenges associated with managing and interpreting big data generated by wearable sensors systems. However, the generation of this data has been based on an assumption that wearable sensor technologies will achieve widespread acceptance and adherence among potential future users. The following sections highlight three primary disincentives against the use of wearable sensor technologies which may hinder their widespread adoption: discomfort and inconvenience, stigma, and privacy.

The first two of these disincentives are both discussed together in the following section, as they are each issues which can be largely resolved using good engineering design. The third disincentive relates to the more philosophical topic of privacy, and is discussed in a subsequent section.

3.4.1 Discomfort and Inconvenience, and Stigma

The first disincentive relates to the comfort and convenience of the device. This involves issues such as device size and placement location (poor placement and large size can discomfort the user), method of affixation and associated difficulty in donning and removing the device (belt, holster, lanyard, adhesive tape, etc.), and requirements to remove the device for bathing or sleeping. In the specific case of recording biopotentials (for example in ECG monitoring or more futuristically for mind control-type applications by way of EEG), attaching electrodes in a reliable manner whilst maintaining a satisfactory signal-to-noise ratio, remains the single biggest limitation. Many of these problems can likely be overcome using good user-centric engineering design approaches.

The second, distinctly different inconvenience, relates to stigma (real or perceived) associated with wearable sensors. While wearable sensors for exercise and activity quantification, such as Fitbit (San Franscisco, CA, USA) and Polar monitors (Kempele, Finland), are currently in vogue, other wearable systems aimed at monitoring conditions associated with aging and poor health may serve as a stigmatizing label for the user and a continuing reminder of their worsened physical condition. Again, clever engineering design may overcome these impediments, creating wearable devices which can be disguised under clothing and which are comfortable and unobtrusive enough that the user is not acutely aware that they are wearing the device.

Taking this notion of engineering a convenient and inconspicuous wearable device to its extreme results in some interesting concepts for future monitoring technologies, which may serve to make the traditional embodiment of a wearable sensor redundant. The following paragraphs provide a brief digression from the main discussion, providing a glimpse of these exciting potential advances, before returning to the discussion of how big data from wearable sensors may impact on privacy.

The most obvious future development which could deliver both a convenient and inconspicuous wearable device is the emerging nexus between wearable sensors and smartphones. Smartphones today are endowed with an impressive complement of inertial sensors, cameras, and communication connectivity. Given the penetration of mobile phones worldwide, the smartphone makes for a very attractive platform from which to perform health monitoring. The major challenge of using a smartphone as a wearable sensor to monitor mobility, activity and wellbeing, is the likelihood of generating poor quality data as a consequence of how the phone is carried (in the pocket or a bag) and because the phone's original intended use hinders how it might be used as a health monitor; for example, using the phone to place a call generates movement which may confuse an activity monitoring algorithm; or the leads of an ECG bioamplifier plugin for cardiac monitoring may impede normal smartphone use. It is conceivable that designs similar to Google Glass (Google, Palo Alto, CA, USA), embodied in a pair of spectacles and responding to voice commands, may also incorporate other MEMS transducers, solving this issue of poor device affixation by requiring that the device is consistently worn at a comfortable location on the body, while also preserving the original usefulness of the smartphone as a communication device. Furthermore, aggregating information from the smartphone as a wearable sensor as well as a communication device may further richen the complexity of the data generated.

The recent emergence of smart watches (such as the Samsung Galaxy Gear, Samsung Group, South Korea), which serve as a wireless peripheral of the smartphone, mostly overcome issues of discomfort and stigma, but at the cost of requiring two devices (both the watch and the phone), and being affixed to the wrist which may introduce significant movement artifact as a result of normal gesticulation.

It is also becoming feasible to consider implanting monitoring devices within the body, which would ordinarily be body-worn. Implantation solves many of the issues mentioned above, but consequentially creates other problems. An advantage of implantable monitors is that correct and comfortable affixation can be assured; small devices may be placed subcutaneously under local anesthetic and fixed in position relative to the body. The user does not need to remember to wear the device and it is also hidden from view, which may alleviate any concerns regarding stigmatization. In addition to the acquisition of commonly sensed inertial signals using MEMS sensors, implantable devices better facilitate the continuous acquisition of other physiological signals, like ECG, respiration, body temperature, and possibly blood pressure. This technology has already been somewhat realized in cardiac pacemakers which monitor ECG and body movement and pace the heart to compensate for increased metabolic demand during strenuous activity [30]; however, pacemakers are obviously only recommendable if there is a medical indication, and there is no capability for continuous or voluminous telemetry streams originating from the device and transmitting to an external data repository. It is this requirement to retrieve the monitoring data which is the largest stumbling block for implantable health monitors; data must be transmitted by radio link across the skin barrier, a process which will quickly deplete the battery when large volumes of data are involved. Given that implantation requires surgery, a minimum battery life of perhaps ten or more years might be suggested. It may be possible to inductively charge the battery, or scavenge power from the body in order to prolong battery life, but these technologies are not yet mature enough for this particular application, although they are fast approaching maturity [31]. Using radio telemetry to retrieve sensor data also places limitations on the distance over which the data may be transmitted, as safe use of radio transmitters within the body will require low-power transmission in order to avoid tissue damage from heating. However, if these technical hurdles can be overcome, the volume and quality of data obtained using implantable sensors would be unprecedented and could revolutionize healthcare. Whether people would wish to be implanted with sensors may ultimately be a personal choice based on the real or perceived risk versus reward afforded by these technologies; for example, the advantages may far outweigh the negatives for those with dementia or a high risk of falling, or those with a genetic predisposition to a life-threatening disease, while a healthy individual may feel no urge to implant themselves with a sensing device.

Another technology complementing the future of wearable sensors as a monitoring modality is the smart environment or smart home [32]. The smart environment also resolves problems of discomfort, convenience and stigma associated with wearable sensors by removing the need to wear any sensor. Environmental sensors, such as cameras, motion sensors, furniture sensors, etc., replace the single body-worn sensor. While not suitable for monitoring electrophysiological signals like ECG, smart environments perform reasonably at monitoring movement, activity and interaction with the environment. Since the infrastructure required to create smart environments is substantially more costly than that of most wearable sensors and potentially more intrusive, it remains to be seen if the advantages provided will offset these costs and disadvantages and make it a viable and acceptable technology for continuous health monitoring in the home.

3.4.2 Privacy and the Quantified Self

The third disincentive to the adoption of wearable sensors involves social aspects associated with continuous surveillance of an individual's location and state of health. Thus far the discussion has largely neglected these issues in favor of exposing the technical challenges facing the deployment of wearable sensors and the interpretation of the data generated. The discussion below is not unique to wearable sensors, and some of these arguments will find analogs in other domains where large amounts of personal data are collected.

One prominent question arising is, "will people tolerate such intensive monitoring of their lifestyles?". The answer to this question depends on the balance of advantages and disadvantages associated with continuous monitoring of lifestyle and wellbeing. If the health benefits are not immediately apparent or impactful, the cost to privacy may be too substantial to incentivize the widespread use of wearable sensor technologies. For example, the use of a fall detection sensor may be a very attractive technology to an older person who has previously fallen and was unable to summon help; however, using sensors for predictive or proactive healthcare monitoring may not carry the same psychological impetus for the user, as the rewards are not immediate, or may simply not be apparent in advance.

Of course, aside from the advantages of monitoring, personal acceptance of, and motivation to use a wearable monitoring system are also influenced by real or perceived disadvantages arising from the existence of extensive information regarding our lifestyles (which is often trusted to a third party). One can cynically consider a dystopian scenario where increased health insurance premiums are quoted to those engaging in unhealthy lifestyles, for example, by failing to meet minimum recommended exercise quotas. There is also the concern of location information being abused to facilitate criminality, allowing burglars to know when people are not home, for example. These concerns are not unfounded given that much of this personal information will be held in cloud storage, where its security is trusted to a third party.

As with any emerging and revolutionary technology, misuses and risks are expected, but ultimately one should remain optimistic that the benefits will ultimately outweigh the disadvantages. However, to protect against such misuses government regulation will surely be required to mandate how data can be legally used and what punishments are appropriate for the various transgressions which will inevitably arise. The boundary between use and misuse of big data truly is a social quandary requiring democratic debate to arrive at a consensus of what is considered acceptable to the majority**.**

As a final comment regarding what has motivated the development of wearable sensor systems, and other such health monitoring systems which involve collection of large volumes of personal data, there is a question of whether these technologies are addressing the symptoms of what are larger social problems. For example, pendent alarms have found popularity as a result of people living longer and often living alone in later life. It is feasible that some of need for intensive monitoring using wearable sensor systems would be obviated if our social fabric was rewoven in a manner that encouraged a return to times when several generations of the family lived together and supported one another. Perhaps the mobility of younger generations and an increasing tendency to follow work around the globe means this is unlikely to occur, and wearable sensors systems are a necessary technology to support healthy aging into the future.

4 Conclusions

Wearable sensor systems have the potential to generate complex, heterogeneous datasets which are currently beyond our capabilities to easily organize and interpret. To successfully utilize wearable sensor data to infer health and wellbeing, and enable evidence-based proactive health management, a coordinated global effort is required to adopt standards and ontologies which allow for data to be shared between research groups, and promote the integration of these data into health information systems. It should be noted that the big data generated by wearable sensor systems may not provide a panacea for outstanding medical informatics problems, particularly those which involve an expensive and time-consuming collection of a gold standard measures of wellbeing, as the significance of statistical inferences derived from any dataset is governed by the number of accurately labelled training examples available. Finally, governmental policy and regulation will be required to ensure that the detailed and personal nature of wearable sensor data is not misused to invade privacies or prejudice against individuals.

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