Wireless Technology in Disease Management and Medicine

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Abstract

Healthcare information, and to some extent patient management, is progressing toward a wireless digital future. This change is driven partly by a desire to improve the current state of medicine using new technologies, partly by supply-and-demand economics, and partly by the utility of wireless devices. Wired technology can be cumbersome for patient monitoring and can restrict the behavior of the monitored patients, introducing bias or artifacts. However, wireless technologies, while mitigating some of these issues, have introduced new problems such as data dropout and “information overload” for the clinical team. This review provides an overview of current wireless technology used for patient monitoring and disease management. We identify some of the major related issues and describe some existing and possible solutions. In particular, we discuss the rapidly evolving fields of telemedicine and mHealth in the context of increasingly resource-constrained healthcare systems.
INTRODUCTION

Although it is difficult to pinpoint the beginnings of wireless health monitoring, its practical roots might be traced back to the invention of the battery by Volta in 1800, the first wireless communication by Dolbear in 1882, and the first electrocardiogram (ECG) by Einthoven in 1906. Einthoven initiated the field of telemedicine by directly connecting an ECG-measurement device, the galvanometer, to telephone lines and thereby transmitting the ECG from his laboratory to a nearby hospital (1). Although only a recent development (in any practical sense), wireless energy delivery is now also becoming a reality. Practical wireless energy delivery is still mainly confined to battery technology, which is a form of noncontinuous semitethered “sneaker-net”-like energy transfer. With these developments, wireless health monitoring became possible.

Wireless medical data transmission has also been driven by a desire to provide remote analysis of physiological data, assuming that resource allocation can be more effective in such a manner. It seems intuitively obvious that it is advantageous to review medical data in this manner in sparsely populated regions or in environments where installing and maintaining wiring is difficult (such as in quarantined regions, across borders, in hazardous locations, or in extremely remote regions). However, it is unclear whether wireless transmission of medical data confers advantages in high-density monitoring environments where healthcare knowledge and resources are plentiful and there are few barriers to direct monitoring. Moreover, there may be advantages to tethered monitoring, if it means that care providers are obliged to interact with the patient more than they otherwise would. One might also argue that continually disturbing the patient with alarms generated by wireless monitoring systems may be detrimental to the patient’s health (2, 3).

An important reason for the introduction of telemedicine is the increasing need to reduce costs. A recent report from the GSM Association and McKinsey (4) warns that, if existing trends in expenditure continue, spending on healthcare will consume an unsustainable proportion of the wealth of developed nations (up to 25% of gross domestic product in the United States, for example), with chronic illness management accounting for 80% of the growth in costs. For example, 210 million people worldwide suffer from chronic obstructive pulmonary disease (COPD) (5), which will become the third-largest cause of death within ten years. Even if smoking ceased today, the effect on COPD statistics would not be seen for up to 20 years (6). COPD is the second most common cause of emergency hospital admissions, with one in eight acute emergency admissions being the result of an acute COPD exacerbation. COPD is also the fifth-largest cause of readmission; 30% of the COPD patients hospitalized in the United Kingdom in one year for treatment of acute exacerbations are readmitted at least once within the following 12 months. As a result, COPD accounts for the second-highest number of total occupied-bed-days in the United Kingdom’s National Health Service. There is evidence that chronic diseases of physical origin also have a large impact on mental health. Along with diabetes, cardiovascular disease, and respiratory-related diseases, mental health problems will present the largest challenges to global healthcare, in both resource-rich and resource-poor settings, over the coming decades (5).

There is some hope that mHealth may provide a way to manage such illnesses and provide a low-cost way of dealing with related
issues such as compliance (4). There is preliminary evidence that telemedicine solutions may be able to reduce the rate of emergency admissions, but this has only been demonstrated in the United Kingdom in studies comprising small numbers of patients. The best results have been reported by the Veterans Administration (VA) in the United States, which showed a 20.7% decrease in health service utilization by a cohort of 1,963 patients; however, this was achieved at a relatively high cost of $1,600 per patient per year (7). The latest systematic review of home telemedicine for COPD showed that existing telemedicine solutions reduce the rate of hospitalization, but patients with telephone support had a higher mortality rate than those in the group that received standard care (8).

There are around 60 telemedicine projects currently running across the United Kingdom’s National Health Service in England alone. Some have demonstrated positive outcomes, although most of these have been small-scale proof-of-concept studies with typically fewer than 100 patients enrolled. There is also considerable variation in the magnitude of the outcomes reported (9).

The case for wireless technology seems far more pressing in resource-constrained locations, such as the rural and peri-urban environments of developing countries. Over the past decade there has been a “leapfrogging” of wired communication systems in such places, where mobile phone technology provides low-cost and affordable communication for almost all of society. Recent estimates indicate that up to 90% of the world’s people are within reach of a mobile phone transmitter, and that the number of mobile phone users is approaching the number of literate people on earth (10). Moreover, the lack of trained healthcare specialists in developing countries, and the migration of such personnel to higher-paying economies, means that there is a pressing need for mHealth, if a financially affordable delivery model can be implemented. In fact, mHealth is beginning to be adopted rapidly throughout both developed and resource-poor economies.

Before discussing this new area of wireless monitoring, we first present an overview of the types of data transmitted and discuss some of the related issues concerning privacy, standards, and evaluation. In particular, we concentrate on ambulatory monitoring of patients in the home (or “biomonitoring”), telemedicine, and recent trends in hospital implementations of wireless monitoring. We also discuss evidence (or lack thereof) concerning the success of such monitoring systems.

BIOMONITORING

A comprehensive review of physiological data measured by biomonitoring is provided by Budinger (11), who describes the various methods with which each parameter has been acquired to date, and the wireless standards by which they are transmitted (and which are still used in contemporary practice). The author concludes that blood pressure (BP), breathing rate (BR), the ECG, and peripheral oxygen saturation (SpO2) are parameters that require “more or less continuous monitoring” in the home, noting that engineering design continues to be limited by the battery life of the equipment. Other parameters that are typically monitored wirelessly include blood glucose, weight, physical activity, and sleep.

In the hospital environment, wireless telemetry has been mostly confined to ECG; (noninvasive) BP and SpO2 have also been monitored in a similar fashion. The main reason for in-hospital telemetry is to grant the patient some freedom of movement (enabling a quicker recovery) and yet allow continuous monitoring for life-threatening events, such as arrhythmias. Typically, a radio-frequency system, such as the hospital’s Wi-Fi network, is used to transmit the data. Recently, several companies have made telemetry systems available in the intensive care unit (ICU). These “eICU” systems vary in functionality but are based on transmission of the standard bedside vital signs (such as the ECG) and on integrating them with other hospital information for display on a remote “dashboard,” allowing the clinician to interact
remotely with the bedside caregivers. A webcam is therefore often also employed. The integration of so much real-time data has facilitated the use of computational predictive alert systems, which have shown some promise, particularly in the lower-acuity setting (12).

Several systems for nonhospital wireless health monitoring have been implemented. Alaoui et al. (13) described the monitoring of congestive heart failure, which affects five million Americans. In congestive heart failure, the heart becomes weak and loses its ability to pump blood throughout the body, resulting in the accumulation of fluid in the lungs. Daily monitoring of weight, BP, and SpO2 is required. The authors describe a secure Internet-based system for transfer of patient data from a home monitoring measurement device to a central station used by clinical staff.

Donoghue et al. (14) described the architecture of a telemedicine system that noninvasively measures BP every 30 min, using mobile phones as a medium between Bluetooth sensors and the central station. Roine et al. (15) surveyed the literature for publications on “telemedicine” between 1990 and 2000. Fifty studies were deemed suitable for consideration, of which 34 assessed clinical outcomes and 16 assessed economic benefit. The authors found that “most of the available literature referred only to pilot projects...and most of the studies were of low quality,” part of the so-called “plague of pilots.” These studies included telediagnosis, in which CT scans are transmitted remotely; those involving home monitoring required patient involvement in order to make physiological measurements. The authors concluded that economic benefits of telemedicine have yet to be proved, agreeing with a criticism previously made in a Lancet editorial (16).

Similarly, Celler et al. (17) noted that “as is common for most telemedicine applications, a strong evidence base for cost effectiveness and improved healthcare outcomes is still not available,” which they attributed to the lack of controlled trials described in the literature. In a review of 175 articles on telemedicine in chronic disease management, these authors found only four that considered cost-effectiveness. Whitten et al. (18) concluded from a study of 551 articles on telemedicine that “only 38 contained any type of real data. Because many of these 38 studies proved to be inadequately designed or conducted, we were unable to perform a traditional meta-analysis.” Mair et al. (19) found that only 29 of 246 studies that mentioned cost as an outcome were suitably rigorous for the purposes of meta-analysis. Agha et al. (20) showed from a study of a one-year telemedicine program in the United States that telemedicine costs (involving teleconsultation, with patients actively involved in vital-sign acquisition) were 58% that of routine care (involving outpatient consultations at a treatment center), and 29% that of onsite care in the patient’s home by clinical staff.

mHEALTH

Although Internet-based systems are increasingly common, a significant growth area is the monitoring of health using a mobile phone. Waves of low-cost or freely downloadable mobile phone applications (“apps”) are beginning to appear, which either process the data on the mobile phone itself or process it remotely after upload to a central server (in so-called “cloud computing” environments). These apps include stethoscopes, sleep structure analyzers, exercise or physical activity assistants, cardiac analysis systems, mental health trackers, and Parkinson’s disease trackers, among many others (21–23). Mobile phones are being constructed to be used with integrated health sensors (24), to interact with external sensors (25), to allow connection to plug-in external sensors (26), or simply to exploit the relatively complex suite of sensors that a typical mobile phone now contains (such as a microphone, camera, GPS, and accelerometer) to provide information on a subject’s health.

However, it is not sufficient merely to collect data. An integrated approach is needed, whereby data are stored in a flexible database and both humans and automated algorithms can parse the data to provide warnings of
deterioration and other actionable information. Many such architectures have been created, ranging from in-hospital wireless ECG monitoring to complex mHealth systems. Celi et al. (27) implemented an open-source telemedicine infrastructure, primarily designed for use in developing countries, which allows upload of any type of medical data to a remote server and synchronization of that data set to an open-source medical record system called OpenMRS (28). The system also allows multiple independent annotations of the data, feedback to the patient or healthcare worker, and annotation with a universal medical lexicon (the UMLS).

The provision of healthcare through using mHealth has several natural advantages over existing care pathways:

1. Lower cost of capital investment
2. Users’ familiarity with devices and interfaces
3. A generic interface that can be easily customized for disadvantaged populations (large icons, voice recognition)
4. Seamless data upload with accurate timestamps and geospatial markers
5. Natural security (led by “mBanking”)—i.e., access requires something you know (a password) and something you have (the device)
6. Use of a private, yet individual, identifier, e.g., International Mobile Equipment Identity (IMEI) number or Media Access Control (MAC) address
7. Allows construction of a long-term medical record, allowing detailed personalized healthcare
8. Automated data upload, no need for user intervention
9. Natural route for data feedback to the user

THE PROBLEMS OF WIRELESS HEALTHCARE MONITORING

Wireless monitoring systems also allow us to address a largely ignored problem in medicine—the fact that we often sample below the “Nyquist frequency,” leading to a phenomenon known as aliasing, which introduces “phantom” effects into the signal when recording data less frequently than twice the fastest change in the data. Nyquist’s sampling theorem states that we need to sample at least twice as fast as the highest frequency in the signal in order to obtain an accurate representation of the information that we are attempting to obtain. A typical example of this is when a wheel on a cart in an old western film picks up speed and starts to rotate faster than 20 revolutions per second. Because the film is being shot at 40 Hz (or frames per second), the wheel starts to appear to spin in reverse. (We can guess that the wheel shouldn’t be spinning in that direction, and apply some extrapolation to fill in the data and make the wheel appear to spin the right way, but we can only do so because it is a simple linear system and we are absolutely sure that the wheel cannot spin backwards! However, in general, we will never know if we have filled in the missing data correctly.) Now set this in the context of current recommendations for home monitoring of BP in the United States by the American Society of Hypertension, which suggest we should record BP twice a day (29). BP normally has at least two peaks and two troughs during a 24-h period (30), so sampling only twice in a 24-h period could accidentally result in measurement of either the highest or lowest excursions of the BP, falsely indicating hypertension or hypotension. It is interesting to note that previous recommendations suggested sampling BP once per day, or less frequently, which is known to have led to overprescription of hypertensive medication due to “white coat syndrome” (a temporary increase in a patient’s BP due to the stress of being examined by a clinician). This syndrome may therefore be sometimes compounded by aliasing. A recent study by Hug et al. (31, 32) demonstrated that hypotensive alarms generated as a result of the monitoring of intra-arterial BP in the ICU were systematically being rejected by clinicians even when those alarms were correct, probably because no immediate review procedure was in place. On average, hypotensive events (which have been linked to poorer outcomes in the
Figure 1

Undersampling mean blood pressure (MBP): continuous measurements (gray line) break a threshold set at 70 mmHg (red dashed line) between $t = [1 \ 2]$ h, while manual measurements (black dots) undersample the blood pressure, and fail to spot the episode of hypotension below 70 mmHg.

ICU) were missed for over 4 h. Figure 1 illustrates this undersampling effect, in which a sampling of the continuous arterial BP measurement at infrequent intervals (black dots) can fail to spot episodes of interest (in this case, an episode of hypotension).

However, increasing the volume of data (and collecting data outside of a medically supervised environment) brings with it four new problems. The first is that without automated analysis, more clinical experts are required to inspect the data. The second issue is that the data obtained from mobile patients are generally noisier and harder to interpret than data obtained from a system in which the patient is not mobile, leading to higher false-alarm rates. The third issue is that as the number of false alarms will increase with increasing quantity of data acquisition, there will be a corresponding increase in follow-up tests and treatments. The fourth issue is that as we start to sample more frequently, we are likely to observe new patterns in the data, with which clinical teams may not be familiar and which they may find difficult to interpret.

A possible solution to the increased volume of work that arises with increasing data acquisition is to increase the level of automation in analysis of the data. Generally, the clinical community has been slow to adopt automatic analysis systems, but this may be because most current monitoring systems are designed to work on a single-channel basis (such as generating an alarm when a single physiological quantity increases above some predefined threshold). When data are fused from several sources, more “intelligent” decisions can be made by automated algorithms, which are more robust in the presence of the uncertainty introduced by movement artifact and sensor noise. When the need for extreme sensitivity (to never miss a serious event) is combined with the single-channel nature of current monitoring, we observe high rates of false alarms ranging from 20%–95% depending on the alarm type (33). Extreme sensitivity means that noise will often trigger false alarms, which can result in alerts being ignored in practice. One solution to this problem is to develop signal-quality metrics for each channel and fuse the data in a manner that dynamically takes account of the underlying trust that can be put in each signal (33–35).

In the hypotension study mentioned above (32) and associated works (31, 33), the authors also showed that hypotensive events could be detected in a timely manner (without increasing the number of false alarms) by using good signal-quality vetting algorithms and automated BP analysis software. The use of signal-quality analysis and automated decision support will become more important as we increase the volume of data and number of patients that we routinely monitor. The clinical task may become one of identifying unusual cases or errors in the automated algorithms, auditing the automation and taking over when there are obvious failures. Of course, with increasing complexity of monitoring, it becomes harder for clinicians to assimilate scores of parameters and reason in many dimensions simultaneously.

A cardiorespiratory monitor produced for the Collaborative Home Infant Monitoring
Evaluation (CHIME) project measures respiration from the impedance pneumogram, heart rate (HR) and HR variability from an ECG, SpO₂ from a pulse oximeter, and sleep position from an accelerometer (36). In a clinical study of home infant monitoring, sensitivity to bradycardia was reported to be 100%, while positive predictivity was 6.5%. The authors concluded that although the system is sensitive to movement artifact, the quality of acquired data (and its breath-detection algorithm) makes it preferable to conventional monitors.

Significant recent advances have been made in noncontact wireless health monitoring. These include using cameras to monitor physical movement during sleep or to extract HR and respiration rate using video data of a patient’s face acquired from webcams (37). Such work has shown promising noncontact measurement of the ECG, which can detect a coarse heartbeat at a distance of several centimeters. Radar has also been used to measure BR and HR in low-power Zigbee-compliant devices such as that proposed by Zito et al. (38) and Scilingo et al. (39), which can be integrated into the fabric of a shirt. Audio and video analysis is also being used to identify sleep-related diseases (21), Parkinson’s disease (22), and depression (23).

DATA TRANSMISSION AND INTERCHANGE

A survey of remote vital-sign monitoring by Meystre (40) noted that “telemonitoring is still overshadowed by teleconsulting and telediagnosis.” Meystre used the term biotelemetry to distinguish the remote measurement of physiological data from other home-based care systems. The author concluded that biotelemetry systems are typically developed in isolation, and that an equivalent to the DICOM (Digital Imaging and Communications in Medicine) standard used by radiologists to transmit images is required. He suggested that this could be based on Health Level 7 (HL7), which was introduced in 1987 for electronic transmission of healthcare data and is currently in its third version. HL7 is based on XML (41) or on the European VITAL standard (42), which specifies formats for transferring vital-sign data. Lebak et al. (43) proposed an HL7-based architecture whereby vital-sign data were collected continuously from sensors by a local server, which periodically uploaded batches of patient data to a remote central server, usable by clinicians.

There are several standards for wirelessly transmitting data, including the battery-hungry high-bandwidth Bluetooth, its low-powered cousin Zigbee, the various forms of Wi-Fi, standard mobile phone voice channels, Short Message Service (SMS), Multimedia Messaging Service (MMS), General Packet Radio Service (GPRS), Universal Mobile Telecommunications System (UMTS), satellite, and even standard radio. Each of these has trade-offs in terms of cost, bandwidth, power consumption, and reliability. Several of these communication methods do not possess error-checking, so data can be lost without the sender knowing. Accurate time-stamping of data is a particularly problematic issue in these circumstances. In medicine, the accuracy of the time at which an event occurred is often important; without it causality can be lost, timely interventions prevented, or erroneous patterns observed that mask events or lead to false alarms. SMS (or “texting”) is particularly sensitive to such issues. Texts sometimes take >24 h to arrive at their destinations, with no guarantee of preserving a given sequence of messages. SMS is therefore only appropriate for a very limited type of transmissions, which are relatively insensitive to missing data and which change on the timescale of weeks rather than days (such as transmissions of a patient’s weight). Time-stamping issues can be solved for systems that have a sampling frequency on the order of a few seconds; the time can be extracted from the mobile phone (which is regularly synchronized with the mobile network) and then appended to the transmission. GPRS and Wi-Fi connections also allow solutions for timeliness and reliability through additions to the communications protocol that explicitly determine quality of transmission (e.g., 27).
Storage is often a combination of binary data (for data acquired at a high frequency, such as ECG) and relational databases (which often store lower-frequency data such as daily weight, or data extracted or aggregated from higher-frequency data). Several standards exist for signals and images, such as the European Data Format (EDF) and the Digital Imaging and Communications in Medicine (DICOM) standard, but no standard exists for relational databases, although examples have been made available with an open-source license (44). Many monitors and systems now exchange data via HL7, as described above. However, HL7 only tells devices how to communicate; it does not encode the semantics of the contained data. For example, a typical transmission could include data concerning a BP measurement (stored as a number using text), a binary ECG snippet, and a diagnosis. The data packet does not specify from which monitor the BP reading came, or whether it was measured invasively or noninvasively, or even from what location on the body the reading was taken (which will change the reading and its interpretation). The ECG may be represented in an arbitrary format, and the diagnosis may appear as free text in any language.

The issues surrounding data formats are relatively trivial to solve if a sufficiently flexible and open format is used such as the Wave Form DataBase format (45). Incidentally, the XML format specified by the U.S. Food and Drug Administration (FDA) is probably not appropriate as a standard because it becomes rapidly cumbersome for the transmission of even moderate recording lengths of ECG data. The issue of unknown sources of data can also be solved easily. An example is the current picture format taken by digital cameras and cameras in mobile phones. Each picture carries meta-information concerning the compression, filters, camera chassis, lens type, resolution, and shutter speed used to take the photograph, along with the time at which it was taken, and the location (if GPS is enabled). To solve the issue of unknown sources would require a change in regulation to require manufacturers to send meta-data in the HL7 packets that specify device configuration, details of any filters applied to the data, and known accuracy. It is also important that signal-quality information is sent with each transmission, since all data are currently treated equally, independent of the actual reliability of the acquisition system used to obtain a given measurement. Most devices have built-in signal-quality evaluation, such as the “movement artifact” in a typical pulse oximeter, but it is extremely rare for devices to provide anything more than a coarse version of the quality index on a visual display. In order to process data accurately, it is important to understand how much each measurement can be trusted. It is almost impossible to differentiate artifacts from real events if only derived parameters are provided (for example, only a BR measurement and not the impedance plethysmography signal used to derive it). When the quality of the underlying signal is accurately estimated, it is possible to use this information to greatly improve the sensitivity and specificity of monitoring algorithms that subsequently use the data (34).

The issue of ontological encoding of data is far more challenging to solve. Although several ontologies exist (e.g., the Unified Medical Language System and its constituent lexicons such as SnoMed, LOINC, and RxNorm), which enable a standardized description of medical data, there is a problem of degeneracy: a given medical condition or intervention can be encoded in multiple ways, making the comparison of medical data time-consuming or impossible. Some progress has been made in this arena by using limited use-specific subsets of given ontologies (27, 44). Unfortunately, the explosion of proprietary systems in the mobile monitoring field has led to a proliferation of ad hoc and proprietary database formats, preventing data from one manufacturer being compared with data from another. A reasonable solution to this problem is to make the database formats available in an open-source manner, and label the categories with an agreed subset of the UMLS. However, manufacturers often allow the customer (i.e., the clinical team) to
extend the database format during use, seriously affecting the ability of automated algorithms to analyze the data.

Two final concerns with wireless patient monitoring are worth noting. First, wireless networks can introduce large delays (sometimes several hours) in data transmission, and so patient data viewed on multiple devices can easily become unsynchronized. Synchronization of databases has long been an issue with distributed software, and techniques from this field may be valuable in dealing with such issues. Second, wireless transmission of data raises issues of patient privacy—particularly the risk of interception of patient data during wireless transmission. The definition of "private" medical data or "protected health information" varies significantly. Some countries have no privacy standards at all, and clinicians transmit patient data via public email accounts without encryption; at the other extreme, even an ECG without any identifiers is considered "private data" in the United Kingdom. The potential for international telemedicine is therefore somewhat complicated.

**QUANTIFYING THE IMPACT OF WIRELESS HEALTHCARE**

Bondmass et al. (46) claimed to have completed the first study of telemedicine for home monitoring that reports clinical and economic outcomes. Patients in this study measured their own vital signs during telephone consultations with nurses. Alarms were generated whenever vital signs exceeded predefined upper or lower thresholds, and these alarms were passed to clinical staff in the study hospital.

De Lusignan (47) conducted a study of 20 patients, wirelessly recording HR, BR, BP, ECG, and temperature, with results collected at a central monitoring station. Vital-sign accuracy was compared with periodic manual measurements made by a nurse. The authors concluded that the objectivity associated with collecting patient data via continuous home monitoring is one of its advantages over systems that require patients’ cooperation in making measurements.

Stewart et al. (48) noted that 1% of the National Health Service budget is devoted to heart failure management, with 60% of this spent on hospital admission. Most patients with heart failure are managed by primary care physicians. The authors emphasized that a ten-minute consultation with a general practitioner is probably insufficient for accurate diagnosis and management of heart failure, and that avoidance of "white coat syndrome" (the anomalously high BP reading that results from the stress of the clinical examination) should motivate the use of home monitoring. The authors conducted a 20-patient study in which check-ups with nursing staff via video conferencing took place once per week.

Woodend et al. (49) conducted a randomized controlled trial testing the effect of three months of care via home monitoring, which collected 12-lead ECG during video consultations with clinical staff. The authors reported improved patient outcomes. Louis et al. (50) surveyed "telemonitoring" methods for patients who have suffered chronic heart failure. At least 30% of patients diagnosed with heart failure upon hospital discharge are readmitted within three months, and up to 54% are readmitted within six months. Admissions are typically prolonged and recurrent. Rich et al. (51) and Stewart et al. (48) showed that daily visits to patients’ homes by a nurse improved patient outcomes and reduced readmission rates. Uncontrolled studies have shown patient acceptability of home monitoring ranging from 80% to 90% and have reported reductions in hospital readmission rates, improvement in patient quality of life, and a resultant overall decrease in annual medical costs due to the reduction in readmission rate. The authors concluded that larger, randomized trials are required in order to confirm these findings. They attributed the benefits of home monitoring to factors such as detecting new-onset atrial fibrillation, persistent hypotension, and overdiuresis (by measuring weight as a measure of fluid balance).
Koch (52) surveyed 578 studies published between 1990 and 2003 on the subject of “home telemedicine,” noting that “most publications deal with vital-sign measurement and audio/video consultations.” The author observed that “publications about... decision support for staff are relatively sparse.” The clinical application domains were mostly in the monitoring of patients with chronic diseases, the elderly, and children. The survey concluded by noting the limitations of home telemedicine, including the lack of standards to combine incompatible information systems, the lack of a framework by which such systems could be evaluated, and the lack of proper guidelines for practical implementation of home monitoring.

A similar survey by Martinez et al. (53) considered 13 randomized controlled trials, 10 nonrandomized controlled trials, and 19 uncontrolled trials or descriptive studies. The authors observed that most of the studies reviewed did not discuss technical feasibility or technical problems. However, these trials used patient-acquired vital signs, and the phrase “continuous vital-sign measurement” was used to denote daily measurements made by the patient using electronic devices (including the ECG; 54). Even among studies based on patient-acquired data, the authors concluded that “there are still few published data on the feasibility and the impact of home monitoring.”

Pare et al. (55) performed a meta-analysis of 65 studies that took place between 1990 and 2006. Of these studies, 18 concerned pulmonary conditions, 17 diabetes, 16 cardiac diseases, and 14 hypertension. The results of this analysis showed that “the magnitude and significance of the telemonitoring effects on patients’ conditions still remain inconclusive for all four chronic illnesses.” The authors concluded that effects on patient outcomes (e.g., decrease in emergency visits, hospital readmissions, and hospital length of stay) were “more consistent in pulmonary and cardiac studies than diabetes and hypertension.” Importantly, although patient compliance was reportedly high in all studies, compliance was seen to decrease through time, which is of concern given that the conditions being monitored are chronic. Little economic analysis was performed in the 65 studies. Most of the 65 studies did not involve randomization, and only 8% included a control group. The majority of studies collected data once per day or once per week and included vital-sign data. The authors also concluded that the quality and reliability of data acquired in the studies were similar to those obtainable by clinical staff, and that, given the weight of evidence provided, future studies need not continue investigating the quality of transferred data. The authors’ definition of “telemonitoring” included measurement of physiological parameters with the active involvement of the patient, rather than entirely passive monitoring. Although the majority of these studies required patients to actively manage their data acquisition, alerts based on univariate thresholds could be generated if measurements were sufficiently “abnormal,” with those alerts then automatically sent to clinicians for attention (56). Some studies (57) have measured parameters continuously using implanted sensors. Outcomes also appear to have improved for patients implanted with a “CardioMEMS” BP-measuring device (58).

A survey of publications on home telemonitoring for respiratory conditions between 1966 and 2007 found 23 relevant studies (59), of which 7 pertained to patients undergoing pulmonary transplantation, 12 were related to asthma sufferers, and 4 involved patients with COPD and other severe respiratory illnesses. Eight of the 23 studies were randomized trials. As in other reviews, these studies required patient intervention in order to perform physiological measurements, which were then transmitted via various means to clinicians.

The case for mHealth in particular has yet to be proven, although evidence is beginning to surface in much the same manner as for more traditional wireless monitoring. Partners in Health have demonstrated that drug stock-outs and overstocking (with consequent improvement in mortality and costs) can be achieved through increasing the speed of transmission of HIV-related data and recording antiretroviral usage (60). Another recent example
is that of Pésinet (61), which uses mobile phones to provide a preventive medical diagnostic for children between 0 and 5 years of age. Local staff in Senegal and Mali use a simple mobile phone interface to enter and transmit information about the infants’ weights and symptoms (e.g., fever) to pediatricians via SMS. The rapid and consistent transmission of data that indicate the early stages of health problems (such as malnutrition) has led to a claimed reduction in mortality (in one group of 300 subjects in Senegal) from 120 per 1000 to 8 per 1000. That is, in over 90% of cases, if the disease is quickly reported, the child will survive (61).

CONCLUSIONS

The landscape of wireless monitoring for disease management is extremely complex and rapidly evolving. Perhaps the most exciting aspects are the newer developments in mHealth. Although the focus is often on visually exciting “apps” developed for the iPhone, many of them are simply cosmetic and add little or no additional value above the ability to review data on a smaller, more portable screen. Interestingly, it is the poorer health sectors (and the associated nongovernmental organizations) that have been driving much of the revolution in low-cost mHealth. The rapid and exciting changes that are occurring in emerging economies, necessitated by economic and environmental constraints, may even provide a model for developed economies to lower health costs and increase efficiencies. The leapfrog effect in wireless telecommunication may translate into a leapfrog effect in medicine. However, large field trials are still required to prove the efficacy of mHealth. Moreover, much of the success of wireless monitoring projects depends on the human intermediaries who control and use the data, and consideration of the human factors is essential for any successful deployment of a wireless monitoring solution.

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

LITERATURE CITED


## Contents

**Huntington’s Disease: Advocacy Driving Science**  
*Nancy S. Wexler*  
1

*Timothy Caulfield and Amy L. McGuire*  
23

**Human Genome Sequencing in Health and Disease**  
*Claudia Gonzaga-Jauregui, James R. Lupski, and Richard A. Gibbs*  
35

**The Genetic Architecture of Schizophrenia: New Mutations and Emerging Paradigms**  
*Laura Rodriguez-Murillo, Joseph A. Gogos, and Maria Karayiorgou*  
63

**CCR5 Antagonism in HIV Infection: Current Concepts and Future Opportunities**  
*Timothy J. Wilkin and Roy M. Gulick*  
81

**New Paradigms for HIV/AIDS Vaccine Development**  
*Louis J. Picker, Scott G. Hansen, and Jeffrey D. Lifson*  
95

**Emerging Concepts on the Role of Innate Immunity in the Prevention and Control of HIV Infection**  
*Margaret E. Ackerman, Anne-Sophie Dugast, and Galit Alter*  
113

**Immunogenetics of Spontaneous Control of HIV**  
*Mary Carrington and Bruce D. Walker*  
131

**Recent Progress in HIV-Associated Nephropathy**  
*Christina M. Wyatt, Kristin Meliambro, and Paul E. Klotman*  
147

**Screening for Prostate Cancer: Early Detection or Overdetection?**  
*Andrew J. Vickers, Monique J. Roobol, and Hans Lilja*  
161

**Targeting Metastatic Melanoma**  
*Keith T. Flaherty*  
171

**Nanoparticle Delivery of Cancer Drugs**  
*Andrew Z. Wang, Robert Langer, and Omid C. Farokhzad*  
185
Eosinophilic Esophagitis: Rapidly Advancing Insights  
J. Pablo Abonia and Marc E. Rothenberg ........................................... 421

Physician Workforce Projections in an Era of Health Care Reform  
Darrell G. Kirch, Mackenzie K. Henderson, and Michael J. Dill .................. 435

Reducing Medical Errors and Adverse Events  
Julius Cuong Pham, Monica S. Aswani, Michael Rosen, HeeWon Lee,  
Matthew Huddle, Kristina Weeks, and Peter J. Pronovost ...................... 447

Relationships Between Medicine and Industry: Approaches to the  
Problem of Conflicts of Interest  
Raymond Raad and Paul S. Appelbaum .............................................. 465

Wireless Technology in Disease Management and Medicine  
Gari D. Clifford and David Clifton .................................................. 479

Geographic Variation in Health Care  
Tom Rosenthal .................................................................................... 493

Deep Brain Stimulation for Intractable Psychiatric Disorders  
Wayne K. Goodman and Ron L. Alterman ........................................... 511

Contemporary Management of Male Infertility  
Peter J. Stahl, Doron S. Stember, and Marc Goldstein ............................. 525

Indexes

Cumulative Index of Contributing Authors, Volumes 59–63 ....................... 541
Cumulative Index of Chapter Titles, Volumes 59–63 ................................. 545

Errata

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