JITTA

JOURNAL OF INFORMATION TECHNOLOGY THEORY AND APPLICATION

ISSN: 1532-3416

mHealth Engineering: A Technology Review

Ulf Gerhardt

Information Management and Information Systems (IMWI), Osnabrueck University

ulfgerhardt@uni-osnabrueck.de

Ruediger Breitschwerdt

Institute for eHealth and Management in Healthcare

University of Applied Sciences

breitschwerdt@fh-flensburg.de

Oliver Thomas

Information Management and Information Systems (IMWI), Osnabrueck University

oliver.thomas@uni-osnabrueck.de

Abstract:

In this paper, we review the technological bases of mobile health (mHealth). First, we derive a component-based mHealth architecture prototype from an Institute of Electrical and Electronics Engineers (IEEE)-based multistage research and filter process. Second, we analyze medical databases with regard to these prototypic mhealth system components.. We show the current state of research literature concerning portable devices with standard and additional equipment, data transmission technology, interface, operating systems and software embedment, internal and external memory, and power-supply issues. We also focus on synergy effects by combining different mHealth technologies (e.g., BT-LE combined with RFID link technology). Finally, we also make suggestions for future improvements in mHealth technology (e.g., data-protection issues, energy supply, data processing and storage).

Keywords: mHealth, Technology, Review, Prototype, Data Transmission, Interface, Portable Device, Embedded Software Application, Operating System, Memory, Power Supply.

Carol Hsu was the Senior Editor for this paper.

1 Introduction

Our interest in an up-to-date scientific mHealth technology overview results primarily from long-term expertise in modeling and supporting several mobile information systems in heterogenous contexts on different continents. Just a few years ago, our standard IS system architecture in technical customer services support simply relied on an Internet connection between a mobile device (rather a laptop than a mobile phone, no sensors) and an immobile integration platform. Almost all data storage and processing took place in that platform (Fellmann et al., 2011).

When we began to make the experiences we gained from engineering product services systems available for the healthcare sector, requirements engineering showed that healthcare professionals would employ applications that run directly on portable devices (Breitschwerdt, Reinke, Kleine Sextro, & Thomas, 2012; Gerhardt, Breitschwerdt, & Thomas, 2015, 2016a). A trend towards mobile applications rose sharply in the following years. Given the increasing complexity of current high-tech products and a large variety of services, we had to develop new methodological approaches, such as a smart glasses-based support system that guides service technicians at the point of service. That system showed a quantum leap in terms of sensor technology and the mobile terminal's data-processing capacity compared to our former technical customer services IS (Metzger, Niemöller, & Thomas, 2017).

In our mHealth projects in developing countries (e.g., in one project, we developed an application to support midwives in Papua New Guinea), we had to face completely different technological challenges. Those challenges concerned offline functionality (lack of steady and stable Internet connection), battery economy, data economy (provider limits data volume to 60 MB) and an integration interface for users with an older 2G phone (Niemöller et al., 2016).

It seems obvious that, in addition to adequate requirements engineering (Gerhardt et al., 2015), successfully realizing such heterogeneous projects requires adequate technological solutions for very different contexts. As information scientists, we believe that reviewing the current state of mHealth technology based on science represents significant scientific value.

Contribution:

In this paper, we review the technological base of mHealth. We use an IEEE-based multistage literature and filter process to "distill" a scientific mHealth architecture prototype. For the resulting mHealth components, we examine the current state of technological implementation. The review also covers the current state of knowledge with regard to synergy effects between different mHeath technologies. We emphasize the need for future improvements in mHealth technology (e.g., data protection, energy supply, data processing and storage).

2 Literature

Parallel to the development of mobile healthcare applications, mHealth research has also undergone a certain evolution. While mHealth research mainly focused on personal digital assistants (PDAs) in its beginnings, the research focus changed towards basic mobile phones from 2007 to 2012 and once again towards smart devices after 2012 (Ali, Chew, & Yap, 2016). Researchers have also described other changes in mHealth research concerning the targeted disease spectrum and also healthcare's accessibility (Ali et al., 2016). Of course, in the mHealth area, some high-quality reviews already exist. However, the recent reviews on the subject of mHealth technology fundamentally differ from our present paper. We can broadly classify them as:

- Reviews limited to specific geographic regions or care structures. These reviews (e.g., Aranda-Jan, Mohutsiwa-Dibe, & Loukanova, 2014; Chigona, Nyemba, & Metfula, 2012) primarily focus on mHealth applications in developing countries.
- Reviews limited to certain diagnoses or patient subgroups. We found several examples of diagnose specific reviews, such as dealing with chronic diseases and elderly patients (Chiarini, Ray, Akter, Masella, & Ganz, 2013), suicide prevention (Luxton, June, & Chalker, 2015), or diabetes management (DeRidder, Kim, Jing, Khadra, & Nanan, 2016).
- Reviews restricted to certain technology aspects. For example, Hall, Cole-Lewis, and Bernhardt (2015) focused on identifying mHealth text-messaging interventions.
- Reviews limited to certain professional user subgroups. Such reviews have targeted, for example, healthcare workers (e.g., Odendaal et al., 2015).

- Reviews of clinical outcome studies. Because mHealth is also a medical subdiscipline, many reviews have also focused on the clinical outcomes of mhealth interventions (e.g., Buntin, Burke, Hoaglin, & Blumental, 2011; Free, Phillips, Watson, Galli, & Felix, 2013; Free et al., 2010).
- Meta-level reviews. These reviews deal with the analysis of mHealth research history (e.g., Ali et al., 2016).

In contrast, in our review, we take a fundamentally different approach by directly focusing on mHealth technology without geographical or patient-/user-related restrictions.

3 Review Method

To obtain an overview of the relevant technological mHealth components, we carried out a multistage search and filter process based on IEEE Xplore. That technology oriented database covers almost two million Institute of Electrical and Electronic Engineers (IEEE) and Institution of Engineering and Technology (IET) journal papers and conference proceedings (see http://libguides.asu.edu/citation/alternatives). Figure 1 graphically depicts the precise research process we followed.

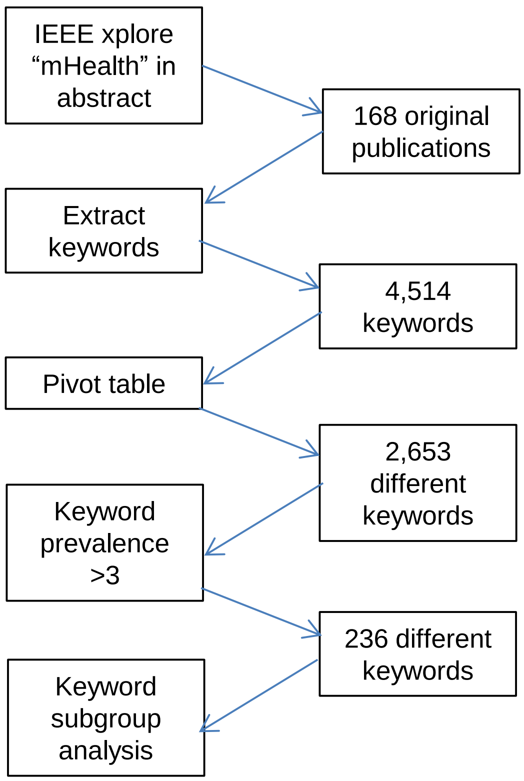


Figure 1. IEEE Xplore mHealth Keyword Analysis

Except for the non-technology-specific keywords, we found the most keywords for the additional equipment and portable device categories followed by the data transmission category, embedded software application category, and memory category. Based on this multistage keyword search and filter process, we developed a prototypical component based mHealth architecture (Figure 2).

Concerning the "memory" component, it made sense to differentiate between internal and external memory. Furthermore, we took the fact that cloud computing comprised an essential component of the "data transmission" keyword subgroup category as a reason to particularly consider third party servers (clouds) with regard to the external data storage and processing component.

In a further research step, we explored the state of scientific IS research with regard to the components that Figure 2 presents. Because the degree of mHealth representation varies quite significantly between different scientific data sources (Gerhardt et al., 2016), we decided to integrate both a biomedical and life sciences database and also an electrical and engineering and technology specific resource into our systematic literature search. IEEE Xplore and PubMed together cover about 27 millionbiomedical, engineering, and technology scientific papers (see http://libguides.asu.edu/citation/alternatives and http://www.ncbi.nlm.nih.gov/pubmed). Throughout that literature research process, the prototypical mHealth architecture (Figure 2) served as a base for the search algorithms. We used both relatively specific and more open search terms (Table 2).

Table 1. Keywords Categories from IEEE Explore mHealth Publications

Keyword subgroup category	Keyword count from that category	Most common keywords
Additional equipment	140	Electrocardiography, wireless sensor networks
Data transmission	64	Wireless communication, cloud computing
Interface	11	User interfaces, medical image processing
Portable device	137	Smartphones, mobile handsets
Embedded software application	47	Middleware, protocols
Operating System (OS)	18	Android, Java
Memory	36	Servers, databases
Non-technology specific	1518	mHealth, mobile computing
Power supply	8	Batteries, power consumption

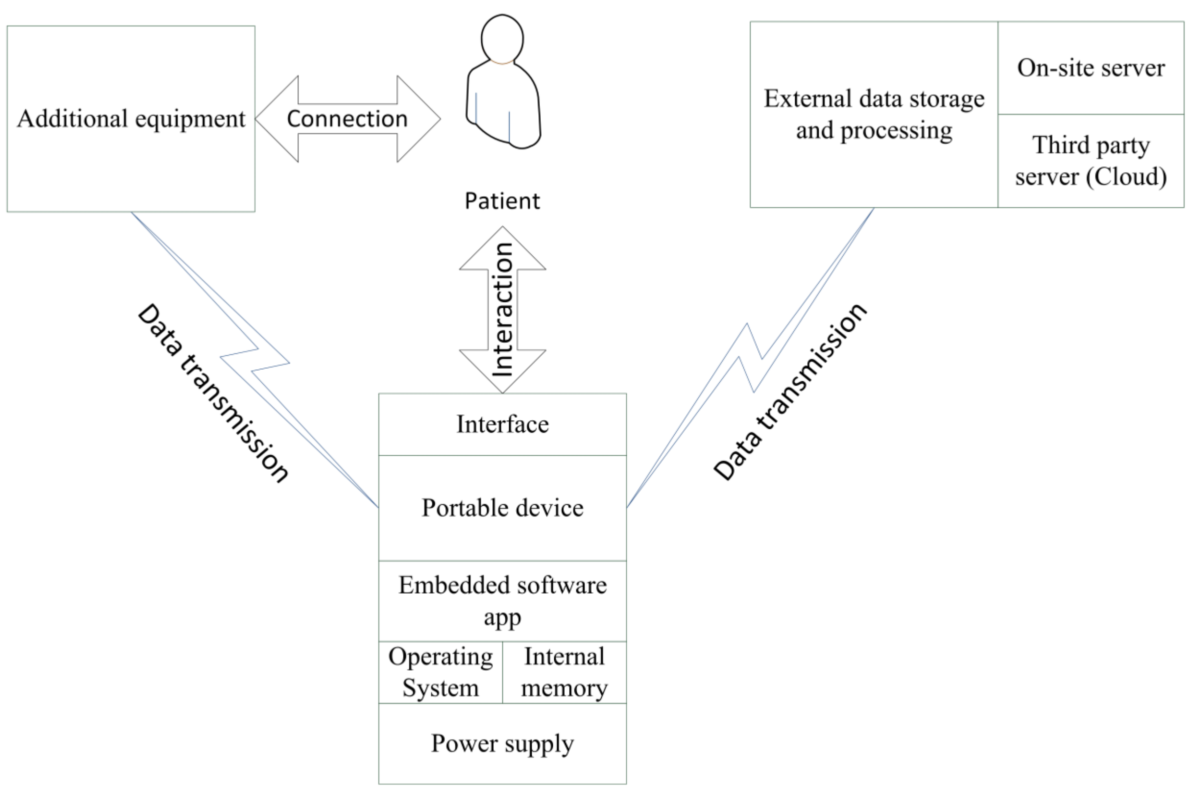


Figure 2. Component-based mHealth Architecture: Prototypical Visualization of mHealth System Core Elements as a Result of Multistep Keyword-based Literature Search

Table 2. Systematic Literature Search: IEEE Xplore and PubMed Search Algorithms

	Search algorithm: mHealth AND…
Specific search terms	LTE, Cat4, Cat6, GPRS, GSM, 3G, 4G, satellite, WLAN, wireless LAN, ad hoc networks, cloud, Bluetooth, mHealth sensors, camera, x-ray, MRI, ultrasound, sonography, computer tomography, radiology, dermatology, Verdict, MeeGo, Maemo, WebOS, Palm OS, Garnet OS, BADA, Windows OS, Blackberry OS, iOS, Android, Symbian, smartphone, tablet, battery
Open search terms	Infrastructure, prototype, hardware, interface, antenna, transmission, software, operation system, psychiatric, psychological, test, localization, power

We then individually analyzed the references we based from using these search terms so that we could extract irrelevant references. We considered references as irrelevant if they:

- Merely described scientific principles without concrete mhealth application
- Contained medical-technological applications without the aspect of mobility
- Did not focus on technological aspects, or
- Contained mostly redundant technological information from multiple former publications.

After that filtering process, 108 relevant and innovative technology publications remained from the systematic literature search. To further increase the sensitivity of the search, we conducted an open search that included the AIS Senior Scholar's basket of journals. Additionally, when we presented an innovative psychiatric mHealth design (Gerhardt et al., 2016a) at the largest German business informatics conference (Multikonferenz Wirtschaftsinformatik 2016), we had the opportunity to discuss mHealth technology aspects with various experts in the information technology theory and application field and to obtain valuable additional hints regarding the AIS Senior Scholar's basket of journals. By this means, the number of papers we obtained rose to 143. Given several similar studies on the same aspect, we focused on avoiding redundancy by selecting the most current, technology-oriented, and detailed studies.

4 Review Results

4.1 Hardware-oriented mHealth Technologies

4.1.1 Portable Device

To achieve a high market penetration, it makes sense to prefer widespread portable systems. Since 2010, the global smartphone market has undergone significant change. While the world market leader resided in Northern Europe in 2010, in 2015, Samsung (320 million units, 22.5% of global market) and Apple (225 million units, 15.9% of global market) took over this leadership position (Gartner, 2016). Table A1 (see Appendix) compares the technical data of various high-end smartphones. From 2015 to 2018, remarkable performance improvements have occurred: for example, the maximum data rate of high-end smartphones increased from 100 Mbps to 450 Mbps, RAM doubled from 2 GB to 4 GB, and battery capacity increasedfrom 2600 mAh to 3600 mAh (Adibi, 2013; AreaDigital, n.d.). According to our literature search, smartwatches, television sets and tablet devices have played only a subordinate role. Tablet devices are used almost exclusively for hospital applications that require a large display. Contemporary television sets also often have Internet access and the possibility to install user-defined applications. Their large screen size offers even better display options compared to smartphones, smartwatches, and tablets—especially for the elderly, deaf, and visually impaired. As such, smart TV-based mHealth applications could arise in the future, such as an application that tracks medicine intake (Yusufov, Paramonov, & Timofeev, 2013), provided that they can meet strict data-protection requirements.

4.1.2 Internal Memory

Some medical imaging methods also require high file sizes due to their resolution. The file sizes for the most commonly used imaging procedures range from 8 MB (e.g., magnetic resonance imaging) to 20 MB (ultrasonic imaging). Therefore, as Adibi (2013) has pointed out, on-device RAM, which should ideally include at least 64 GB (in exceptional cases, such as digital mammography, even more) represents a main limitation for mHealth biomedical imaging data transmission. We provide more details about the on-device RAM in current high-end smartphones in Table A1.

4.1.3 Regular Smartphone Sensors and Additional Equipment

In a 2009 review on mHealth and eEmergency systems, Kyriacou, Pattichis, and Pattichis (2009) found that most applications dealt simply with transmitting electrocardiography (ECG) or image/video. Since then, the mHealth landscape has exponentially developed and differentiated both in terms of smartphones' and tablets' "on-board equipment" and with regard to additional external sensors:

4.1.4 Modified Application of Regular Equipment

Microphone: normally, microphones in a mobile phone only transmit spoken communication for telephone calls. However, microphones can obviously collect other biological sounds and background noise as well, such as voices, breath sounds, and other noises such as water flow noise (tsunami), explosion noise (large fire), or rumbling sounds (earthquake). A smartphone application or analysis software can then analyze these sounds. These features transform the mobile microphone into a valuable ingredient of a smartphone disaster recovery system (Adibi, 2015). Furthermore, one can use the smartphone microphone as an "uncalibrated pressure sensor". One can transform this pressure data, which a microphone collects when a person forcibly exhales, into an "uncalibrated flow rate". From this flow curve, one can calculate the essential parameters of a pulmonary function test (i.e., PEF, FEV1, FEV1%, and FVC) with a deviation of 11.74 percent from spirometric reference measurements (Agu et al., 2013; Larson, Lee, Liu, Rosenfeld, & Patel, 2013). In a similar direction, another mHealth application can accurately detect coughs in an audio recording (Agu et al., 2013; Larson et al., 2011). In addition to coughing, a smartphone can detect sneezing and snow blowing via a microphone (Agu et al., 2013; Chen, Wang, & Chu, 2012).

Speakerphone: one can also use a smartphone's speakerphone (just like the speaker system of other mobile systems, such as a tablet) in emergency situations to, for example, transmit important information and instructions from military or civilian rescue organizations simultaneously to more than one listener. As an additional requirement for that communication pathway, Adibi (2015) has identified the special importance of long-term evolution (LTE) for direct communication between mobile end devices since it bypasses the base station in a disaster scenario (see also Section 4.2.3).

Earphone: Poh, Kim Goessling, and Swenson (2012) present another elegant way to use modified standard smartp[hone equipment. Considering aesthetics, comfort/wearability, costs, and possible irritation from adhesive electrodes, they decided to integrate reflective LED/photosensors into the earbuds of popular intraconcha earphones that allowed 400 Hz photoplethysmographic waveform registration from the subcutaneous blood vessels of the tragus region. One can transmit the corresponding dataflow either via cable and processing/control unit into an iPhone or via 2.4 GHz radio transceivers with USB connector into a tablet. These so-called "heartphones" outstandingly match the heart rate measurements of a clinical ECG (mean bias −0.07 beats per minute).

Camera: smartphones and tablets can transmit detailed optical information using their integrated camera(s). According to the idiom "a picture is worth a thousand words", photos (that an image analysis software possibly supports) provide a quick and detailed overview of the nature and intensity of an emergency and the number of affected persons, and they allow one to identify individual persons that a disaster has affected (Adibi, 2015). Furthermore, applying independent component analysis on the color channels of a video signal allows one to precisely detect heart rate, heart rate variability, and respiration rate (Agu et al. 2013; Poh, McDuff, & Picard, 2011). In addition, mHealth applications can even detect melanoma disease with a sensitivity of 87.27 percent and a specificity of 71.31 percent by applying standardized dermatologic diagnostic criteria to skin photographies taken with a smartphone camera (Agu et al., 2013; Wadhawan et al., 2011). A comparison between three experienced wound clinicians and an mHealth application in terms of how well they assessed wound sizes yielded a correlation coefficient of 0.736 (Wang et al., 2015). While Wang et al. used a special "image capture box", several other wound-assessment mHealth studies (Poon & Friesen, 2015; White, Podaima, & Friesen, 2014) have used standard smartphone equipment to detect wounds' size. Of course, one can also use mobile phone cameras for video conferencing, which can give patients the chance to contact, consult, and/or receive support from their personal physician. Finally, smartphone cameras can also read QR codes. For example, Vazques-Briseno, Navarro-Cota, Nieto-Hipolito, Jimenez-Garcia, and Sanchez-Lopez (2012) used this function as an alternative to RFID for tracking childrens' food intake in a mHealth platform.

LED light source: high-end smartphones have a LED light source close to their camera. During a heart cycle, a pulse wave passes through the entire blood vessel tree and leads to a rhythmic dilation and contraction of the vessels. A smartphone can measure the resulting pulsatory opacity changes in a human's fingertip tissue if an individual places a fingertip on the lamp and the camera at the same time (Zhu, Wang, & Meng, 2013).

Acceleration sensors: most mobile devices can detect linear accelerations (accelerometer) and angular/rotational velocities (gyroscope) via micro-electro-mechanical systems (MEMS), micrometer-small devices that measure either capacity changes/the piezo effect that the deformation of a spring causes or the deflection of magnetically excited comb structures (tuning fork principle). These acceleration sensors detect both controlled and involuntary movements of the smartphone carrier. Therefore, they may help one in discovering emergency situations that often feature relatively rough involuntary movements (e.g., epileptical seizures, earthquakes) or deliberately controlled movements (e.g., enabling a person to escape from an earthquake situation) (Adibi, 2015). Due to the fact that individuals can more reliably attach a watch than a smartphone to their body, smartwatches appear particularly useful in that context. Ghazal, Al Khalil, Dehbozorgi, and Alhalabi (2015) recently showed that the mHealth application they developed could detect falls with 93 percent accuracy using accelerometer and gyroscope data from smartwatches. These smartwatches were connected via Bluetooth to a smartphone, which then alerted the caregiver via Wi-Fi, SMS or Bluetooth. Of course, accelerometers can also simply estimate walking speed. In this context, the combination of accelerometer and GPS data may further minimize errors in the walking speed estimation (Altini et al. 2014).

Compass: compasses rely on the orientation of magnetic particles in parallel with the terrestrial magnetic field, which makes it possible to determine a cardinal direction. Given additional information, such as the position of visual landmarks, a compass allows for an application to relatively accurately determine a smartphone's position and determine routes. These compass properties supplement the smartphone´s accelerometer and the gyroscope, especially when major disasters occur (Adibi, 2015).

GPS: first of all, in combination with accelerometer data, the GPS signal can improve the accuracy with which a smartphone estimates speed (Altin, Vullers, Van Hoof, van Dort, & Amft, 2014). Furthermore, one can obtain valuable epidemiological information by combining medical data with its corresponding GPS position. Boonchieng, Boonchieng, Senaratana, and Singkaew (2014) empirically proved that, by systematically acquiring household GPS coordinates and combining it with individual health data, socioeconomic information, and Google Street View data, they could obtain both descriptive statistical results (e.g., age range of a district population, number of people living with each disease) and also the exact geographic distribution of certain diseases (e.g. patients with chronic kidney disease) (Boonchieng et al., 2014). This information has particular value when deciding how to best distribute health resources (e.g., in choosing where to build a new hospital or in analyzing which disease will consume particular medications).

Received signal strength indicator (RSSI): an elegant way to localize people in their apartment involves measuring the signal quality of their apartment's Wi-Fi network, which smartphones routinely measure. Duarte, Yokoyama, and Villas (2015) show that, with appropriate calibration, an mHealth application could measure this signal quality with 97.75 percent accuracy. Such an mHealth application could be particularly valuable for patients with paroxysmally altered consciousness (e.g., epilepsia) but also for dementia patients. In both cases, the application would be able to safely detect a change in the typical movement pattern and to generate an emergency call autonomously.

Sensor-free sleep monitoring: standard smartphone sensors provide a characteristic pattern of user habits based in particular on the type and intensity of smartphone use, charging processes, and environmental sensor perceptions such as brightness or loudness level. The best effort sleep (BES) model considers light sensor data, duration of phone lock, phone recharging times, phone off times, accelerometer data, and microphone data (Chen et al., 2013). Compared to on-body-sensor sleep-estimation systems (sleep duration error: 10 minutes), BES showed a considerably larger and also clinically relevant measurement error (> 40 minutes) (Chen et al., 2013b). Thus, from a medical point of view, one can use BES only as a screening method and not to definitively diagnose a sleep disorder.

4.1.5 External Devices

ECG/seismocardiography (SCG): due to the high prevalence of cardiovascular disease and the lack of ECG side effects, the ECG is one of the most common medical examination methods.

- Gakare, Patel, Vaghela, and Awale (2012) showed that, via Bluetooth, a mobile sensor can transmit ECG signals to an Android-based smartphone application, which then analyzes the signal in real time (e.g., heart rate variability) and then, depending on the wireless network coverage, either stores or transmits the results via cellular link to a server that, in turn, forwards them to a physician. Many mobile ECG (mECG) applications have employed this “two-hop wireless relay scenario” (Song, 2011; see also Figure 6).
- Many other authors have also described Bluetooth-linked ECG sensors for real-time ECG telemonitoring (e.g., Secerbegovic, Mujcic, Suljanovic, Nurkic, & Tasic, 2011, Yang, Ge, Li, Rao, & Shen, 2014).
- Furthermore, researchers have shown another Android/Java-based smartphone application linked to a Bluetooth ECG device (Shimmer, Dublin, Ireland) to achieve a high sensitivity (92.7%) and positive predictive value (94.0%) in atrial fibrillation screening (Oster et al., 2013).
- Watanabe, Kawarasaki, Sato, and Yoshida (2012) have pointed out that the Lithium-ion battery capacity (450 mAh) of the Shimmer Bluetooth ECG device can provide up to 36 hours of ECG recording.
- Etemadi et al. (2016) recently presented a 9 x 4 cm ECG and SCG patch with 50 hours battery capacity (not counting not counting the battery power that an optional antenna consumed) that one can affix to the chest wall using three surface ECG electrodes.

An unsolved problem in this context concerns the fact that the diagnostic value of an ECG increases with each lead while the freedom of movement of the patient decreases with each cable attached. A clinical standard ECG provides 12 leads (via 10 electrodes). To date, even high-end mHealth ECG systems do not include more than seven leads (recorded via five electrodes fixed to the patient) (e.g., Huang et al., 2014). A desirable goal would involve developing a body area network with patch electrodes and patch antenna (see Figure 7) embedded in comfortable garment that provides a clinically meaningful 12-lead ECG without the need to attach 10 cables to the patient.

Besides the electrophysiology, acceleration sensors can also measure the mechanical aspects of a heart’s action by registering chest-wall microvibrations (SCG).

SIM card-based medical record bracelet/pendant system: under certain circumstances (e.g., accidents, dementia, epilepsia, stroke, cardiac arrest), being able to immediately access an individual's medical history can save the individual’s life. An mHealth personal medical record system provides access to a patient's information via a medical database stored on a 16 KB SIM card in a protective bracelet/pendant system with an easily recognizable logo. The Extensible Markup Language (XML) file—stored up onto the SIM card using an USB interface SIM-card reader/writer—includes general information (e.g. name, telephone number, blood type), medical history (e.g., surgical, obstetric, allergies, medication), medical encounters (e.g., chief complaint(s), present illness, physical examination) and other relevant medical data (e.g., orders and prescriptions, test results, medical images). The custom-developed “Medirec” software application allows one to reproduce this information on a standard mobile phone (Nokia 5630 XpressMusic Symbian, Nokia Corp., Espoo, Finland) (Abu-Faraj, Chaleby, Barakat, & Zaklit, 2011).

Pill dispenser: based on an ordinary medication blister, researchers have developed mHealth blister systems with microcontrollers and a NFC-based air interface (Morak, Schwarz, Hayn, and Schreier, 2012; Crema et al., 2015).

Peak flow meter/spirometer: as we indicate above, one can use a smartphone’s microphone as “uncalibrated pressure sensor” to register an “uncalibrated flow rate” and the corresponding derived parameters (i.e., PEF, FEV1, FEV1%, and FVC) (Agu et al., 2013; Larson et al., 2013). One can expect an even higher precision when one uses calibrated medical devices. Therefore, Al-Dowaihi et al. (2013) connected a calibrated peak flow meter via Bluetooth to an Android mobile application that directly displays suitable information to the patient and—via the Internet—transmits data to healthcare professionals. Researchers have also developed a similar mobile spirometer architecture based on iOS/iPhone 5s (Michailidis, Smanis, Stamatis, Bergeles, & Kouris, 2014). Furthermore, an impressive project from Oxford University and Harvard Medical School developed a mobile spirometer that meets both medical accuracy requirements and developing countries' limited financial resources. The mobile spirometer—including both breathing tube (autoclavable) and hardware elements (printed circuit board, USB 2.0 port, differential pressure sensor, digital humidity/temperature sensor, microcontroller, 12 Mhz oscillator)—costs about US$11.75 and meets American Thoracic Society (ATS) and European Respiratory Society (ERS) standards (Carspecken, Arteta, & Clifford, 2013). This successful project shows mHealth's potential for developing countries.

Pulse oximeter: pulse oximetry non-invasively obtains a pulse curve and the blood oxygen saturation by measuring the absorbance of infrared light transmitted through human body tissue (usually finger or ear lobes). Obviously, the heart's beat and oxygen saturation represent vital bodily functions. Therefore, pulse oximetry has an extremely high priority in human medicine. For sparsely populated areas or developing countries, the ability to convert such an important medical technology into mHealth would mean a quantum leap forward in medical care. Therefore, pulse oximeter mHealth systems that display heart rate and blood oxygen saturation on a smartphone display via Bluetooth have become quite popular (e.g., Wuryandari & Suprijono, 2012). One particular system (called the phone oximeter project) has also included photoplethysmogram waveform and signal quality index (depicted as background color) (Dunsmuir et al., 2014). A quite elegant system that comprises a smartphone (stored in a bracelet), its headphone microphone (placed next to the nose), and a pulse oximeter (connected to the smartphone via Bluetooth) can detect moderate or severe obstructive sleep apnea (OSA) with an accuracy of up to 92.2 percent (Behar et al., 2015).

Accelerometer: of course, contemporary smartphones and smartwatches include an accelerometer by default. Individuals widely use these accelerometers when playing sport as a step counter. However, to achieve greater accuracy, one may also link external accelerometers to a smartphone as well. For example:

- The Lab of Mobile Health in Peking University, Beijing, China, fit a triaxial accelerometer in a wearable belt. Connected via Bluetooth transmission to a smartphone-based Android application, the system reached a higher accuracy to monitor walking and stair climbing compared to the "iPhone Health" system (Liu, Wu, & Hou, 2015). In addition, the "intelligent belt system" could dial an emergency contact number and to send a short message that contained GPS information when a user shakes the intelligent belt in an emergency situation (Liu et al., 2015).
- Furthermore, Lennon, Bernier, Tamayo, Goldberg, and Mankodiya (2015) have presented a multisensory wearable sensor system for monitoring more discrete movement disorders such as dyskinesia.
- Yang et al. (2014) fixed an accelerometer to a wheelchair to detect rollovers.
- Li, Huang, Xu, Hu, and Xie (2014) implemented a three-axis accelerometer, a three-axis gyroscope, and a three-axis compass into a Bluetooth-enabled (and RFID-enabled for user identification) wristlet and achieved a recognition precision of 93 percent.
- Interestingly, our systematic literature review revealed several mHealth systems that have drawn conclusions from physiological parameters to mental processes. For example, Saleheen et al. (2015) combined a complex respiratory rate sensor (see respiratory rate paragraph below) with an additional three-axis gyroscope and three-axis accelerometer on each wrist and achieved an accuracy rate concerning cigarette puffing detection of 96.9 percent with only 1.1 percent false negative results.
- Furthermore, Shi et al. (2015) transmitted data about breath rate, heart rate, ambulation pattern, and skin temperature from a chest strap and smart shirt via Bluetooth to a smartphone to predict alcohol cravings.

Pressure cushion: the Wuhan University of Technology has integrated a resistive pressure sensor into a wheelchair cushion in order to determine if and when its user has fallen out of it (Yang et al. 2014).

Blood pressure device: Rebolledo-Nandi, Chávez-Olivera, Cuevas-Valencia,Alarcón-Paredes, and Alonso (2015) replaced the manometer of a common sphygmomanometer with a MPVZ5050GWTU pressure sensor (Freescale Semiconductor, Inc., Austin, Texas), processed the sensor signals via microcontroller unit (MCU ATMEGA328PPU, Atmel Corp. San José, California), and wirelessly transmitted the serial protocol information via Bluetooth (C-06 Bluetooth module, Wavesen, Guangzhou, China) to an

Android-based mobile device. Similar blood pressure systems are quite popular (e.g., Wuryandari & Suprijono, 2012). Some other blood pressure meters, such as UA-767 Plus NFC (A&D, Tokyo, Japan), support the NFC technology. This technology allows even patients who do not read and write (e.g., in pediatric oncology) to correctly capture their blood pressure and heart rate to a mobile device simply by touching the measurement device with their smartphone (Duregger, Hayn, Morak, Ladenstein, & Schreier, 2015).

Respiratory rate: Pimentel et al. (2014) showed that one can also accurately calculate the respiratory rate from an oscillometric blood pressure signal with their “AutoSense” respiratory rate sensor. However, this sensor combines different information from a wearable chest band, a two-lead ECG, a respiratory inductive plethysmograph band, galvanic skin response measurement, a skin temperature thermistor under the arm, ambient temperature sensor registration, and an artifact assessment via a three-axis accelerometer. For data transmission, AutoSense uses an ANT ultra-low power wireless network solution (Ertin et al., 2011).

Libra: beyond its cosmetic or long-term medical implications, body weight also has short-term implications for some patients (e.g., patients with chronic kidney disease or oncological patients). Individuals can readily access body weight scales with NFC technology, such as UC-321PL (A&D, Tokyo, Japan) (Duregger et al., 2015), which enable them to rapidly acquire their body weight without error. Such scales also provide a practical way for children or illiterate persons to obtain their body weight.

NFC-based touch area network: Duregger et al. (2015) showed that individuals—even children in preschool—can capture their own wellbeing, pain level, and nausea simply by touching a smart poster that features child-friendly symbols and corresponding RFID tags on the back with a smartphone. To farther facilitate this process, the researchers used a passive NFC booster antenna on the back of a smartphone (Duregger et al., 2015).

Electroencephalography (EEG): due to registration channels it requires, EEG places particularly high demands on data transmission (Byrne, Manada, Marinkovic, & Popovici, 2011). Therefore, according to our knowledge, currently no “mEEG” exists.

Bed occupancy sensor: in the geriatric sector and in home nursing care, mHealth facilitates remote patient monitoring. A particularly unobtrusive system (BOS by S4 Sensors Controls.) uses bed pressure mats (Joshi, Holtzman, Arcelus, Goubran, & Knoefel, 2012). These mats, equipped with 24 pressure sensors, rest below the mattress and provide not only information about at what periods the mat is covered but also a two-dimensional impression of the movement pattern when a patient leaves the bed. This feature has high practical relevance since the mats can differentiate the movement pattern when patients unintentionally fall out of the bed from normal standing up. Furthermore, the mats also measure a patient’s respiratory rate (Joshi et al., 2012).

Heart rate (HR) and heart rate variability (HRV): many commercial devices deliver such precise measurements—particularly HR measurements—that researchers have successfully used them for scientific purposes, such as BioHarness 3, a Bluetooth-based chest belt that can detect posture transition and associated heart rate response (Zephyr, Annapolis, Maryland) (Jovanov, Milosevic, & Milenkovic, 2013). As another example, Sannino, De Falco, and De Pietro(2014) used BioHarness 3-derived HRV to detect obstructive sleep apnea (OSA) events. His algorithm performed better than five well-established other OSA event-detection systems.

Fetal Doppler signal: contemporary obstetrics commonly monitors fetal heart activity. The fetal Doppler ultrasound (US) can reliably detect fetal emergency situations and, thereby, prevent intrauterine deaths or hypoxic brain damage (which result in permanent mental and physical impairment). Kazantsev, Senin, Ponomareva, and Mochalova (2014) presented a fetal-monitoring system architecture in which a U.S. Doppler probe (which a pregnant woman can easily use herself) connected to an Android-embedded Doppler Web monitor that linked further to the cloud and, finally, to a gynecology and obstetrics specialist. Via an appropriate data-compression algorithm, they achieved a transfer time that took only 10 to 11 seconds (107 byte recordings of fetal Doppler output signal; home Wi-Fi network throughput 32,000 kbit/s) (Kazantsev et al., 2014). For pregnant women in industrialized countries, a mHealth system would make fetal monitoring more convenient; for pregnant women in developing countries, mHealth could potentially represent the only way to ensure optimal antenatal care.

Environmental/ambient sensors: knowledge about patients’ environmental conditions plays a crucial role in medically assessing them. Although contemporary smartphones feature environmental sensors as standard (e.g., for light and temperature measurement), these sensors cannot continuously provide ambient conditions at a sufficiently valid enough level partly due to the varying way people transport (e.g., in a phone holder vs. the trunk of a car) and store (e.g., close to the body vs. in a handbag or backpack vs. in a bookcase) their phones and partly due to the indirect way smartphones detect temperature (i.e., via battery temperature). Thus, commercial sensor boards have arisen (e.g., MTS310CA from Crossbowtechnology) that validly measure ambient light, temperature, acoustics (Crossbowtechnology, 2003; Navarro, Lawrence, & Lim, 2009).

mHealth laboratory diagnostics: for mHealth laboratory diagnostics purposes, Balsam has developed an orthographic projection capillary array fluorescent sensor that achieves comparable measurement results to a smartphone camera and a commercial fluorescence plate reader (Balsam, Bruck, & Rasooly, 2013).

Other biomedical sensors: one can connect any available biomedical sensor to a portable device. The IEEE has proposed standard protocols (IEEE P 11073) for the following application profiles (Adibi, 2015): ECG (P11073-10102), implantable cardiac device (P11073-10103), pulse oximeter (P11073-10404), heart-rate monitor (P11073-10406), blood pressure monitor (P11073-10407), thermometer (P11073-10408), respiration rate monitor (P11073-10413), weighing scale (P11073-10415), glucose meter (P11073-10417), insulin pump (P11073-10419), body composition analyzer (P11073-10420), peak expiratory flow (P11073-10421), cardiovascular fitness (P11073-10441), independent living activity (P11073-10471), and medication monitor (P11073-10472). The possibility to combine not originally mobile standard devices with wireless networks opens up enormous additional mHealth opportunities. In this context, Jara Zamora-Izquierdo, and Skarmeta (2012, 2013) presented an innovative device that combines RFID/NFC-technology for contactless user identification, standard interfaces (USB/RS232/IrDA) to connect non-mobile devices, and the networking technology 6LoWPAN (IPv6 over Low-Power Wireless Personal Area Networks) with a Jennic transceiver to connect to the cloud and/or the Internet of things.

4.2 Data Transmission

We discovered few mHealth architectures that used ZigBee (Liu et al., 2012) or ANT (Zhang, Passow, Jovanov, Stoll, & Thurow, 2013) to transmit data from a sensor to a mobile device. In the context of our systematic literature search, we most frequently (e.g., in Postolache et al., 2011) encountered the prototypical data transfer architecture that Figure 3 depicts.

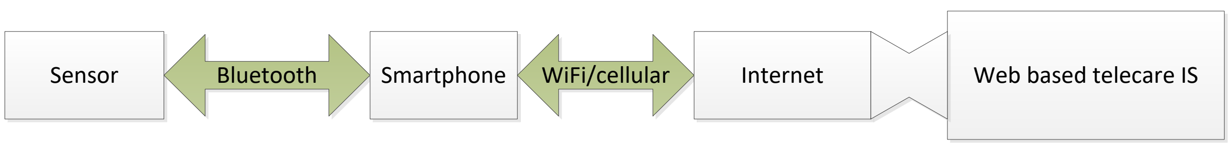
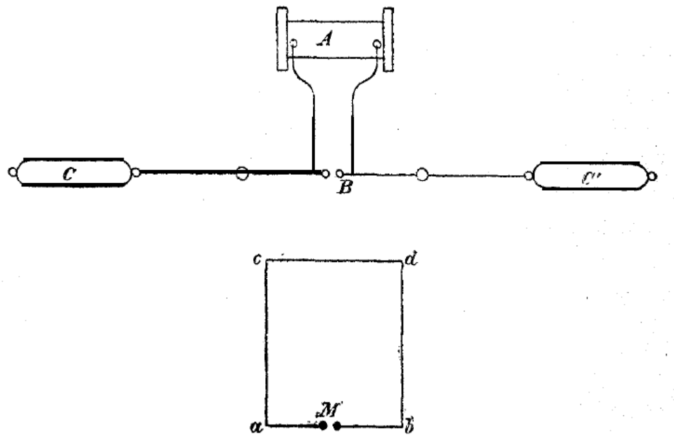


Figure 3. Prototypical Two-hop Data Transmission Architecture

In this section, we discuss the corresponding data-transmission technologies (e.g., Bluetooth and Wi-Fi) and also common alternative options. As we mention above, mHealth can overcome geographical distances between medical professionals and patients, between medical professionals and their colleagues, and between professionals/patients and medical databases. Therefore, the wireless range constitutes an important characteristic of mhealth systems.

The basic principle of wireless data transmission dates back to the 19th century when Heinrich Hertz (1984) experimentally demonstrated that pulsatile electrical discharges connected to a dipole induce electric power flow in a copper wire over a certain distance (see Figure 4) due to electromagnetic waves. The wavelength λ and the frequency f of these electromagnetic wave are reciprocally interconnected: $\lambda = c / f$ (Steute Schaltger™te, 2010). In this equation, c refers to the vacuum velocity of electromagnetic waves, which is identical to the speed of light. However, even under vacuum conditions, only a small part of the radiated transmission power reaches the receiver.

The principal factors that affect the ratio between transmission power and received signal intensity in vacuum are distance (quadratic relation), frequency (quadratic relation), and effective receiving/sending surface of the receiver/transmitter antenna (Steute, 2010). Normally, smartphones and many wireless sensors use planar inverted F-shaped antennas (PIFA). Today, special vertically polarized BAN antennas have emerged as an alternative to the classical horizontally polarized PIFA antennas (see Figures 5 and 6). These new antennas have an improved radiation efficiency (from < 20% (PIFA) to > 80% (BAN)) (Dumanli, Gormus, & Craddock, 2012). Furthermore, mHealth developers have to consider other factors such as natural electromagnetic background noise or (outside a vacuum) materials that absorb or scatter electromagnetic radiation. In this context, another important aspect concerns the data-transfer rate from the sensor to the portable device (sensor-manager link technologies; see Section 4.2.1 below) and from the portable device—via a base station (e.g., Evolved Node B) to the external data storage and processing unit (cellular link technologies; see Section 4.2.3 below). In this section, we discuss sensor-manager link technologies, wireless body area networks (WBAN), and cellular link technologies.



A/B: Ruhmkorff inductor/interrupter
C/C´: ends of the dipole
M: spark micrometer

Figure 4. A Short History of Antenna Design: Fundamental Principle for how Electromagnetic Waves Transmit (Hertz, 1894)

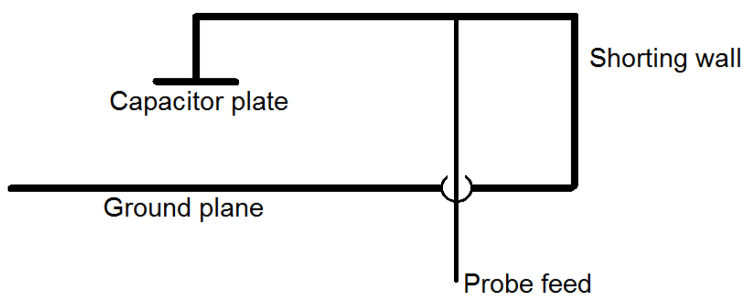


Figure 5. A Short History of Antenna Design: Planar Inverted F-Shaped Antenna (PIFA) (based on Nashaat et al., 2005)

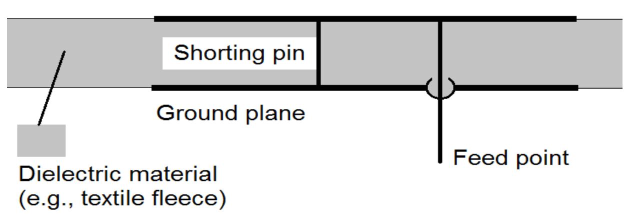


Figure 6. A Short History of Antenna Design: Patch Antenna (based on Ullah et al., 2009)

4.2.1 Sensor-manager Link Technologies

The mHealth concept refers not only to the wireless data transfer but also to cable-free mobile devices. Thus, mHealth devices must also adopt a wireless power supply. Accordingly, battery life represents another important characteristic of mHealth systems. Figure 7 depicts these three characteristics (i.e., wireless range, data-transfer rate, battery life) of the most common mHealth sensor-manager link technologies.

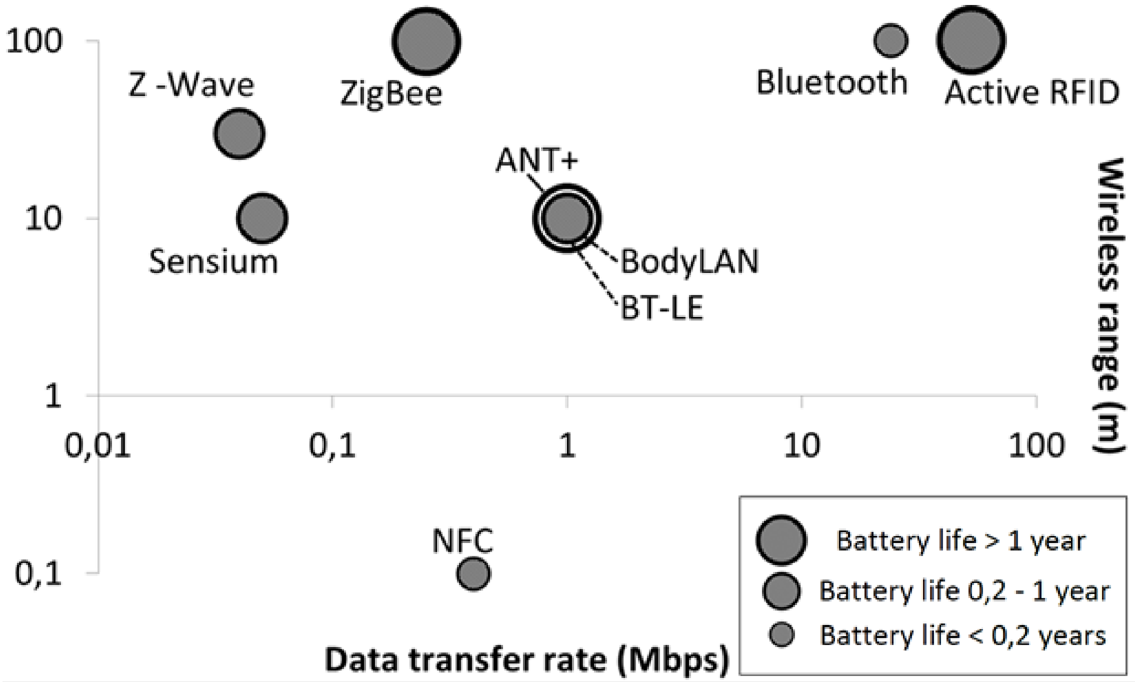


Figure 7. Main Characteristics of Common mHealth Sensor-manager Link Technologies: Wireless Range, Data-transfer Rate, Battery Life (data in accordance with Adibi, 2012, 2013, 2015; Atmel Corporation, 2014; Song & Isaac, 2014; Jacinto, 2009; Sharma, n.d.; Smiley, 2016)

Based on Figure 7, we recommend that one differentiates mHealth sensor-manager link technology in the following ways.

Long range–low rate: a cluster of sensor-manager link technologies do have a relatively long wireless range that, presumably due to their rather low data-transmission rate, operate for months or even years without an external power supply: Sensium, ANT+, BodyLAN, Z-Wave, ZigBee, and Bluetooth-Low Energy (BT-LE). These link technologies are proprietary low-power sensor technologies that the medical and other fields (e.g., sports and wellness) already use (Adibi, 2012; Gehlot, 2012). In this technology cluster, the degree to which a link technology is suitable for mHealth purposes varies according to its performance characteristics (Figure 7 and Table 3).

While ANT has seen common use in leisure sports, it has not seen similar use in professional mHealth technology—possibly because Apple does not support the technology (Zendesk, 2018). Further, few smartphones feature ZigBee due to its relatively high price (Song. 2011). Therefore, in our literature review, we found few mHealth architectures that focused on ZigBee (Liu et al., 2012). While significantly cheaper than ZigBee, Z-Wave does not suit simultaneous audio and video transmission due to its significantly lower data-transmission rate. In contrast, BT-LE can simultaneously process multiple medical devices due to its relatively long wireless range and relatively high data-transmission rate that allows for a timed synchronization scheme (Adibi, 2012). Furthermore, BT-LE has gained much importance through the fact that it constitutes one of the physical transport layers of the constrained application protocol (CoAP) that enables personal health devices to access home networks and the Internet (Santos, Almeida, & Perkusich, 2015). In contrast to Bluetooth, BT-LE has a much longer battery life of one year. These technologies also differ in their security and privacy aspects. ZigBee, BT-LE, and ANT+ qualify for use in the healthcare sector because they meet safety standards and feature appropriate encryption technologies, wheras Z-Wave does not (Adibi, 2012).

Table 3. "Long Range–Low Rate" Link Technologies: Application-related Properties and Safety Standards

Technology	Properties	Safety standard*
Z-Wave	Relatively inexpensive Low data-transmission rate (see Figure 7) No simultaneous audio and video transmission	–
ZigBee	High price Not very common in smartphones Not common in mHealth	+
ANT+	Not supported by Apple Not common in mHealth Common in leisure sports	+
BT-LE	Simultaneous multiple devices processing Timed synchronization scheme enabled High data-transmission rate	+

* + = high safety standard available, – = safety standard not sufficient for health sector.

We can distinguish two other subtypes of sensor-manager link technologies from this first "long range–low rate" cluster: 1) Bluetooth and active RFID and 2) NFIC.

Bluetooth and active RFID: both Bluetooth and active RFID have a long wireless range of up to 100 metres and with an impressive data-transfer velocity of up to 24 Mbps (Bluetooth) or 54 Mbps (active RFID) (Sharma, 2016; Adibi, 2012). However, serious technical reasons have precluded these technologies from spreading in the mHealth sector: Bluetooth systems consume a relatively large amount of power and have a correspondingly low battery life and, thus, seem not suitable as mHealth-related link technology. However, Bluetooth low energy (BT-LE) has elimintated this disadvantage (see long range–low rate paragraph above). Due to the necessary high-performance battery, active RFID units have a considerably larger size and weight than passive RFID units and cost between US$20 and US$100. For this reason, they see use primarily in tracking large assets (pipes, containers, and machinery) but not in the mHealth sector. However, one can use passive RFID to compensate for Bluetooth's major disadvantage: its long-winded pairing procedure. Hayn, Jammerbund, and Schreier (2011) have proposed a way to combine passive RFID and Bluetooth: by putting a mobile device near the ECG recorder, a field detector can switch on the ECG recorder's Bluetooth module while an RFID tag fixed onto the ECG recorder delivers the Bluetooth pairing information. We think that one could easily implement this model into other medical sensors or devices and, thus, expand many classic healthcare elements with an mHealth component. While few smartphone models support RFID, almost all contemporary high-end smartphones have a Bluetooth interface. One way to address the fact that few contemporary smartphone models support RFID involves combining Bluetooth and passive RFID technology in another way: with IDBlue (IDBLUE Corporate Headquarters, St. John's, Canada), a pen-shaped device that can read RFID information and transmit this information to other devices (e.g., smartphone) via Bluetooth (Vazques-Briseno et al., 2012).

NFC: Figure 7 shows that NFC differs from all other communication technologies due to its very low range (0.1 metres). Therefore, NFC has so far typically seen use in card readers and peer-to-peer (P2P) communication (Adibi, 2012). However, NFC will soon establish itself as a standard smartphone technology and, thus, gain importance for the mHealth sector. For example, Morak et al. (2012) successfully developed a "smart blister" system. Based on an ordinary medication blister, microcontrollers tracked when someone removed pills from the blister. They used mobile phones to collect the data from the blister´s NFC-based air interface.

4.2.2 Wireless Body Local Area Networks (WBAN)

Another very interesting wireless approach uses the human body itself or the electric field around the human body for data-transmission purposes. One can establish the WBAN connection between sensors and the human body either directly ("galvanic coupling approach") by directly attaching two transmitter electrodes to the human body that subsequently becomes "a special kind of transmission line" or indirectly via electric field induction ("capacitive body coupling technique") (Mazloum, 2008).

Electromagnetic waves can propagate parallel to special inductive surfaces. These surfaces can serve as a conductor layer with a dielectric film coating or as a flat conductor with a corrugated surface form (Wait, 1957). Turner, Jessup, and Tong (2012) demonstrated that one can create a “surface wave garment” that enables over-body propagation at 60 GHz WBANs. Of course, changes in body shape or composition can affect the data transfer in WBANs. Therefore, researchers have attempted to better understand this body-coupled communication (BCC) channel. For example, Attard and Zammit (2013) demonstrated the influence that different body movements have on the BCC channel’s characteristics. The WBA network comprises various nodes. A personal device acts as a coordinator node: it interacts with the user and combines all information from the other nodes. One can divide the other nodes into sensors and actuators.

Whereas the sensor nodes measure and forward physiological or ambient data, actuators can convert information into physical motion (e.g., inject a specific volume from an insulin pump) (Movassaghi, Abolhasan, Lipman, Smith, & Jamalipour, 2014). The WBAN nodes usually connect to each other wirelessly. Table A2 (see Appendix) depicts the common WBAN transceiver categories (physical layer specifications according to the IEEE 802.15.61 WBAN standardization (Kwak, Ullah, & Ullah, 2010; Kartsakli et al., 2014).

4.2.3 Cellular Link Technologies

In this section, we discuss the predominant cellular link technologies. Of course, any cellular link technology can be only as effective as the associated wireless coverage (i.e., its range) (see Figure 8).

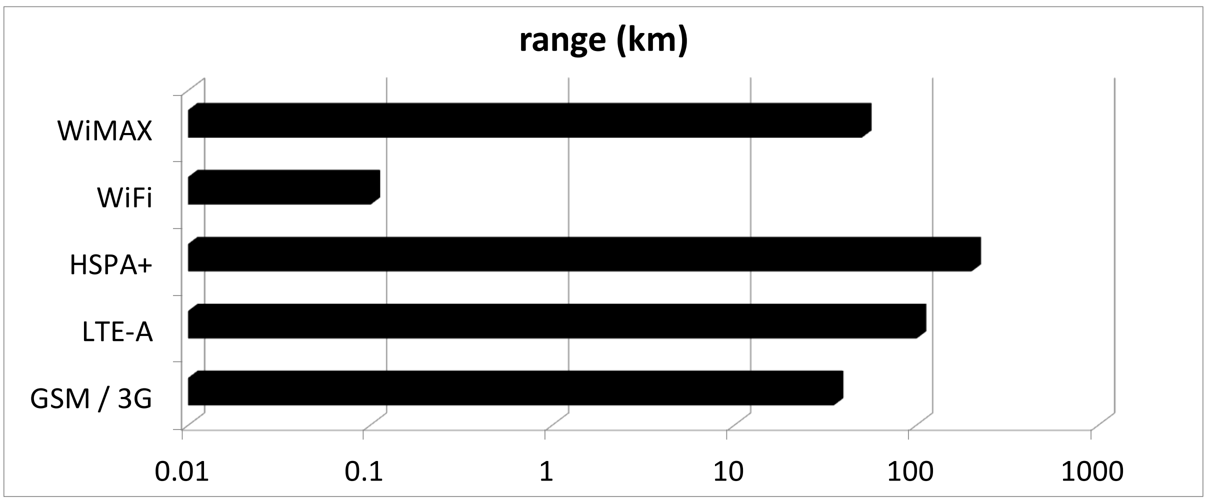


Figure 8. Range of Cellular Link Technologies

Therefore, before designing an mHealth study, one needs to carefully analyze wireless coverage. For example, Brown et al. (2015) conducted a cartographic analysis of mobile communication antennas and towers (CAAT) and improved the sent/received success rate of an SMS-based mHealth project from 97.84 percent to 100 percent simply by choosing the best location (signal strength) of the SMS system and by choosing the best provider (most service antennas).

GSM/3G: the Groupe Spécial Mobile (GSM)—an ad hoc subgroup of the European Conference of Postal and Telecommunications Administrations (CEPT)—started to harmonize the European cellular technologies in the 1980s. Later, the European Telecommunications Standards Institute (ETSI), a European Union Standards Organization, and later the 3rd Generation Partnership Project (3GPP) technical specification group called GSM/EDGE Radio Access Network (GERAN) continued this work (3GPP, 2018). When considering GSM architecture from the perspective of a mobile device (e.g., smartphone), the mobile device connects to a base transceiver station (BTS). Equipped with radio frequency (RF) antennas, transceivers, duplexers, and amplifiers, a BTS enables wireless communication between mobile devices and a cellular network. Its supraordinate network node (i.e., the base station controller (BSC)) determines the actual “cell” configuration, controls important physical properties of the BTS (e.g., RF power levels), and connects to the mobile services switching center (MSC). The MSC acts like a “telephone switching office”: it controls inbound and outbound calls and manages data traffic. One BSC can control many BTSs. The MCS has access to several network databases, which include the home location register (HLR), which stores permanent information about subscribers; visitor location register (VLR), which stores temporary information about visiting subscribers; authentication center (AUC), which stores ID authentication and encryption parameters; and equipment identity register (EIR), which stores information about the equipment's ID. The gateway mobile services switching center represents the interface between the MSC and the global telephone network (landline/mobile network) (Islam, n.d.). 3G technology offers a data throughput of about 2 Mbps (Lehr & McKnight. 2003). From a global perspective; GSM remains the most widely used cellular link technology (Islam, n.d.).

LTE-A: the performance of a data-transmission channel depends on its data-transfer rate and latency. The 3GPP focused on meeting its stakeholders' data-rate and service-quality demands by developing LTE (3GPP, 2018b). This popular technology offers a transmission speed of 300 Mbps for downloads and 75 Mbps for uploads and has very low latency (about 5 ms). It suits cell sizes between 10 meters and 100 km. Based on the well-known relationships between wavelength, propagation velocity, and frequency of electromagnetic waves, a lower frequency selection can achieve a longer wavelength with a correspondingly greater range. Each state in the United States uses a specific predetermined frequency band list: 450, 700, 800, 850, 900, 1700, 1800, 1900, 2100, 2300, 2500, 2600, 3500, and 3600 Mhz (Adibi, 2015). Adibi (2015) has also pointed out that, in case of a disaster scenario, LTE can circumvent the base station and allow direct communication between mobile end devices.

HSPA+: high-speed packet data access (HSPA+) constitutes another 3GPP release. It combines high-speed down link packet data access (HSDPA) and enhanced-up link (UL) (Wannstrom, 2018). However, comparative measurements between LTE and HSPA+ show that, despite a lager average network radius, LTE can serve significantly more users with a significantly higher average network throughput and total network traffic (Jacinto, 2009). Accordingly, customers show a higher satisfaction with LTE than that HSPA+ (Jacinto, 2009).

Wi-Fi: Wi-Fi refers to a brand name for a popular short-range wireless connection technology whose specifications the IEEE 082.11x regulates. Due to its low coverage (20 meters indoors and 100 meters outdoors) around the access point (Song & Isaac, 2014), Song (2011) and Song and Isaac (2014) have justly designated Wi-Fi as a "wireless extension to Ethernet" and Wi-Fi access points as "network island[s]", respectively. These statements point to Wi-Fi's core restriction: it does not suit standalone use in vehicles (cars, subways, buses) and, therefore, allows (although wireless) no veritable "mobile" Internet access. We list further relevant Wi-Fi features, especially with regard to differences between Wi-Fi and World Interoperability for Microwave Access (WiMAX), in Table A3 (see Appendix).

WiMAX: The IEEE 802.16 standard defines WiMAX's characteristics. Its high data-transmission range (up to 50 km) (see Table A3 in the Appendix) represents its most significant difference to Wi-Fi. This range allows the technology to cover a network area ten times larger than 3G towers can achieve (Song & Isaac, 2014). However, it has a somewhat lower data-transfer rate (up to 70 Mbps) (Song & Isaac, 2014).

Hybrid cellular networks: in contrast to Wi-Fi, 3G and WiMAX offer real mobile data connections. 3G's main advantage probably lies in the investments already made into it and also in the fact that it remains more established in terms of voice communication (Ma & Jia, 2005). Considering its technological equipment, we may find that WiMAX will prevail in the long term over 3G. Wi-Fi, however, seems unbeatable with respect to bandwidth and data-transmission rate (see Table A3 in the Appendix). Therefore, we agree with the statement that "WiMAX and WiFi are strongest when working collaboratively…[and that] a practical way of having WiMAX and WiFi joint networks is to use WiMAX to link up WiFi hotspots" (Song & Isaac, 2014).

4.3 Third Party Server

Figure 3 depicts a prototypical mHealth data flow. In addition, note that, while external data storage affects telecare IS, it may also—depending on the system's architecture—include a (temporary) storage and data processing in a cloud. Thus, mobile cloud computing (MCC) seems to be particularly noteworthy in the data storage and processing context. In MCC, mobile devices connect wirelessly to a central processor, which produces an Internet connection to a "cloud". In that cloud, a "cloud controller" ensures that a data center adequately answers the mobile terminals' requests (Dinh, Lee, Niyato, & Wang, 2013). To date, the MCC has a valuable significance for mHealth applications: for example, it allows wireless broadband patient monitoring, the effective coordination of an emergency vehicle fleet, low-threshold access to healthcare information, and healthcare payment operations (Dinh et al., 2013; Varshney, 2007). In our opinion, the most comprehensive definition of cloud computing comes from the National Institute of Standards and Technology (NIST) (Mell & Grance, 2011). Figure 9 summarizes the NIST definition's key points.

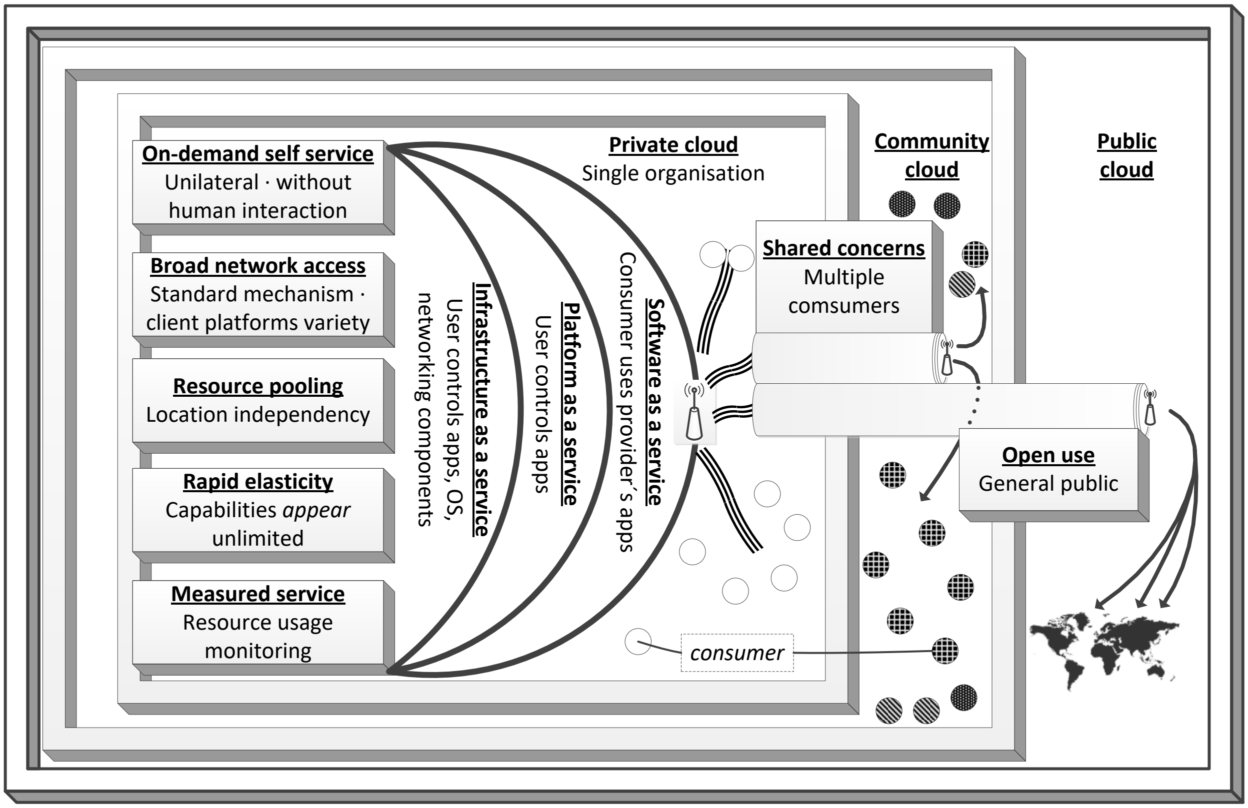


Figure 9. Characteristics of Cloud Computing in Accordance with the NIST Recommendations (Mell & Grance, 2011)

According to the NIST definition (see Figure 9) (Mell & Grance, 2011), cloud computing provides a quantum leap to mHealth engineering because it allows a wireless, localization-independent, and uncomplicated on-demand access from different user platforms (smartphone, tablet, personal computer, special equipment) to quickly recruitable and (seemingly) unlimited computing and storage capacities. NIST's definition uses the terms software as a service (SaaS), platform as a service (PaaS), and infrastructure as a service (IaaS) to distinguish the degree to which customers mobilize a cloud's resources. While, in Saas, customers may only use the applications that the provider has already preinstalled in a cloud, in PaaS, they can install applications themselves. Finally, in IaaS, customers can install or modify a cloud's OS or networking components. Furthermore, one can differentiate a cloud based on access. Different users from same organization can access a private cloud, various users from different organizations who share certain concerns (e.g., security requirements) can access a community cloud, and the general public can access a public cloud without any restrictions. Hybrid clouds refer to those clouds that mix the above three types.

As it concerns cloud data storage and processing, we question the use of online social media to remotely monitoring patients' health. We agree in this respect with Khorakhun and Bhatti (2014, p.290) who refuse to use Facebook for mHealth systems with the following argumentation:

> *The privacy, security and access control mechanisms must remain under the control of the carer network, but in the Facebook platform, the policies are controlled by Facebook and could change arbitrarily. Also configuring security and privacy features is complex, and so erroneous configuration is possible.*

To exchange electronic health records between different health professionals in a standardized way, a continuity of care record (CCR) usually uses the Extensible Markup Language (XML). Correctly reading and presenting XML files, however, requires appropriate analysis software, the "parser". Chen, Liou, Chen, and Li (2013a) recently experimentally tested the speed of different XML parsers by creating CCR objects between 1 and 40000 kilobytes. They showed that the Simple API for XML (SAX) worked the fastest, though Javascript Object and Array notation (JSON) followed closely behind. However, they found

XML Document Object Model (DOM) had a much slower speed and that they could not recommend it (Chen, Liou, Chen, & Li, 2013a).

Table 4 overviews further relevant challenges in processing and storing mHealth data and possible approaches to solve them.

Table 4. Medical Data Processing and Storage: Challenges and Appropriate Approaches to Solve Them (in accordance with Clifford & Clifton, 2012; U.S. National Library of Medicine, 2016)

Challenge	Appropriate-solving approach
Biotelemetric image transmission standard	Health level 7 (HL7): protocol standard for the communication of clinical information systems at application level
Time-stamping issues	Use GPRS or Wi-Fi communication protocol Extract time stamping information via synchronization with the smartphone telecommunications network
Semantic encoding of biomedical data	Supplement the HL7 content with metadata (e.g., device configuration, applied filters, signal-quality information) Apply the Unified Medical Language System (UMLS) Semantic Network tool (semantic types/semantic relations)
Ontological encoding	Apply the UMLS vocabularies (CPT, ICD-10-CM, LOINC, MeSH, RxNorm, SNOMED CT) and natural language-processing tools
Time delays in data transmission	Database-synchronization techniques
Patient privacy issues	Ideally develop an international standard for data security

4.4 Power Supply

Table A1 (see Appendix) shows the performance characteristics of typical smartphone batteries. Whereas the popular low-power mHealth sensor-manager link technologies mostly have a battery life of several months or even years (see Figure 7), even high-end smartphones with above-average battery capacity reach only about 1200 minutes (20 hours) of battery life during active use (AreaDigital, n.d.).

In developing countries in particular, an insufficient power supply can constitute a major cause of mHealth failures. For example, Eskenazi et al. (2014) developed an mHealth application to map the indoor locations that mSpray users had sprayed with insecticides to combat malaria and found an insufficient power supply to most commonly cause mHealth non-use ("phone was not charged or battery died", 47.6%). Therefore, in the absence of a continuous power plant-operated electricity network as in in developing countries, one may need, for example, photovoltaic plants to independently recharge smartphone batteries.

WBAN technology has critical applications concerning mHealth energy efficiency because mHealth sensors must be portable and unobtrusive (i.e., small and light), which limits their available battery capacity. Nevertheless, implantable WBAN sensors require a long battery life (Marinkovic & Popovici, 2012). In this situation with rather small battery volume and particularly high demands on battery life, a possible solution would involve reducing the amount of electricity that the sensors consume. To this end, Marinkovic and Popovici (2012) developed a wake-up receiver (WUR) with a static power consumption of only 270 nW. The actual sensor consumed no energy in its sleep mode, but a signal from the master node could always wake it up. A smartphone's audio output could provide power supply for external sensors. Yao, Sun, and Hall (2015) achieved between 77.9 and 85.4 percent efficiency with a tunable impedance-matching network. However, even under these optimal conditions, the audio output harvest reached only 20.5 mW, which satisfies what many sensors require (e.g., pulse oximetry) but does not meet ECG-registration requirements (Yao et al., 2015).

4.5 Interface

A workgroup from the Sydney University of Technology created an extremely user-friendly graphical interface in 2009 for supporting registered nurses (RN) in emergency situations (Sax & Lawrence, 2009). This example shows the importance of appropriate requirement engineering to successfully develop mHealth applications. Beforehand, they conducted semi-structured interviews with the potential stakeholders to understand the normal course of a medical emergency situation. Based on the knowledge they required, they designed appropriate IS support for each working step a RN performs in an emergency situation. To summarize their work, they found that an appropriate mHealth emergency interface needs:

- A logical structure
- Access to the required information with the minimum of operation steps
- A space-saving input device
- To reduce cognitive effort
- To reduce the number of buttons
- The most natural, intuitive human-machine-interaction
- To automatically display critical parameters
- A clear graphical structure to display content on the screen, and
- Acoustic and visual feedback (Sax & Lawrence, 2009).

Taking also non-emergency conditions into consideration, Matthew-Maich et al. (2016) described the following mHealth interface design features:

- **Software/app features**: graphs that display patient-related trends, a notification system for alerting professionals, motivational and exucational text messages, reminders to improve treatment adherence, video messaging, client-management features, visual/auditive/cognitive help, patient-texting features, and voice over Internet protocol (VoIP) software applications.
- **Hardware/mobile devices**: mobile devices with large touchscreens and large virtual buttons, stable mobile device systems, lighter devices, touch pens, voice input function, and cloud computing resources (Matthew-Maich et al., 2016).

In addition to graphical and information technology aspects, the degree to which a user interface (UI) helps users to search for information represents a major UI property. Traditional search engines presuppose a very structured approach via a well-informed, focused use of keywords that fits to an a priori known research object. However, medical personnel often work under time pressures and psychological strain, especially in emergency situations. Under such circumstances, mHealth applications should actively help individuals search for information. For this purpose, information systems use semantic computing. Similar to the association areas in the cerebral cortex, semantic computing associates multidimensional information with a keyword and, thus, can sense a user's actual intentions beyond the lexical meaning in the keywords they use. The "content descriptors" as a basic element in Figure 10 may require further explanation: content descriptors may include on the one hand structural (e.g., spatial, storage format, encoding, browsing options, temporal or syntactic description) and on the other hand semantic (in particular "real world" semantics) aspects of information.

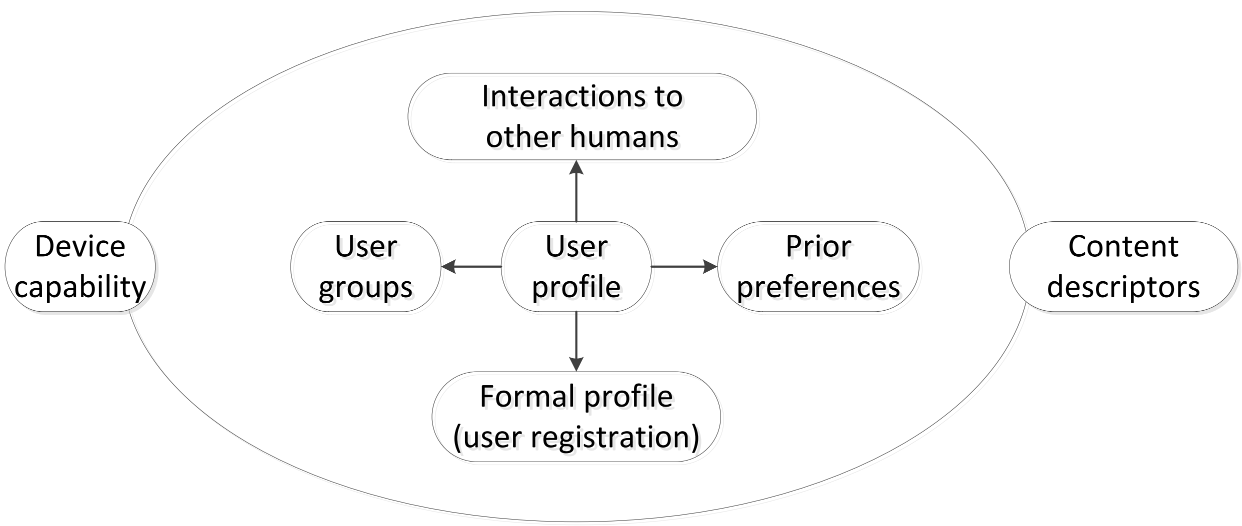


Figure 10. Main Semantic Pieces of Information (in accordance with Bellini, 2012; Hasida, 2007)

Since semantic computing accesses multidimensional and users' private data, safety aspects play an important role in safeguarding that data (especially in medical software applications). However, we do not focus on these aspects in this overview. However, as Azfar, Choo, and Liu (2015) note in discussing the possibilities to locate and restore mHealth users' details, email addresses, locations (with an associated timestamp), food habits, passwords, four-digit PINs (e.g., that users use to log into applications), and user profile pictures, one needs to carefully consider data security aspects when developing mHealth applications.

4.6 Software-oriented mHealth Technologies

4.6.1 Operating System (OS)

Common operating system (OS) platforms include Android, BlackBerry 10, Cyanogen Mod, Embarcadero, Fire, Firefox, iOS, Jolla/Sailfish, Tizen, Ubuntu, and Windows (Würstl, 2016). Based on data from 5,000 mHealth practitioners (e.g., app developers and decision makers) and approximately 11,000 mHealth apps, evidence shows that Android and iOS will remain the preferred OS in the near future (Research 2 Guidance, 2015). Cecere, Corrocher, and Battaglia (2015) also support this finding. As such, we compare the main features of Android and iOS in Table A4 in the Appendix.

Wukkadada, Nambiar, and Nair (2015) compared iOS and Android in detail and found that iOS development makes more specific demands on the hardware while Android development "can take place in any modestly equipped computer science laboratory". In economic terms, Android (as freeware) offers an advantage compared to iOS. On the other hand, iOS has a much better error-reporting feature, which provides live support to users. While Android has minor security gaps, iOS features an excellent level of security that makes an antivirus program unnecessary. As such, Wukkada et al. (2015) came to the overall conclusion that "iOS is better than android but…cost wise [that] android is better".

Blackberry OS provides a free instant-messaging service; on the other hand, the Blackberry market is almost exclusively restricted to the business sector, so that the Blackberry app market offers a much lower number of apps for one to download (Raman, n.d.). Jolla Sailfish OS offers innovative design and handling but a quite limited app supply in the Jolla store. Emulated Android apps run slowly and inadequately on Jolla. Furthermore, limited privacy settings and sometimes confusing handling may further explain Jolla Sailfish OS's low market share. Users familiar with Android systems should have no problems with handling Firefox OS. The Firefox app store has a comparatively low number of apps, and they often simply link to Web-based resources rather than provide real, installable apps. However, this system's advantage—"to blur the line between the Internet and locally installed apps"; Wimmer, 2015)—seems to have become a disadvantage today (based on user ratings) since one can buy memory cards more cheaply than access the Internet. The Cyanogen Mod OS resembles Android in design and handling, but it adds various intelligent features to the Android portfolio (e.g., an optional control scheme, especially for left-handers) and access to millions of apps in the Google Play Store. Cyanogen also features enhanced data security in that it allows one to completely encrypt a smartphone's storage. In summary, Cyanogen Mod seems to represent a realistic alternative to Android OS. However, at present, it features a low number of original apps (Wimmer, 2015). Ubuntu, a Linux-based OS, not only provides a similar user interface on desktop and smartphone but also allows one to use the same apps on different devices. Due to its open source code, security holes and spyware may be detected more quickly than other OS.

4.6.2 Embedded Software App

The most widely used Android OS use Java as their common programming language, though some use C and C ++. Individuals who program iOS applications usually use Swift and sometimes also Objective-C, C, and C++. Other possible programming languages include HTML5 (for Blackberry, Jolla/Sailfish, Tizen, and Ubuntu OS), PHP (Cyanogen Mod OS), Object Pascal (Embarcadero OS), CSS (Firefox, Web OS), Qt und QML (Jolla / Sailfish, Ubuntu OS), ActionScript (Macromedia Flash Lite), and Python (Ubuntu OS) (Würstl, 2016). The core of an information system usually comprises several specific layers that the open systems interconnection model (OSI) depicts (see Figure 4). Roughly speaking, this model comprises four data-oriented layers (that deal with microelectronic bit transmission, data encoding and protection, network, and data transport) and three application-oriented layers (Tari & Bukhres, 2001). As one can see in Section 4.1.5, a large variety of devices with wireless connectivity exists. Healthcare practitioners often simultaneously use many on the same patient. Therefore, the architecture of a mobile app has to face "the challenge of multiple simultaneous health data sources" (Borodin, Zavyalova, Zaharov, & Yamushev, 2015). The corresponding software layer, which mediates these various parallel processes, is called middleware. Middleware is anchored to the three application-oriented OSI layers (i.e., that focus on controlling, presenting, and directly applying communication) (Tari & Bukhres, 2001). As an example, we mention the cloud-centric middleware platform SOPHRA (Lomotey, Jamal, & Deters, 2012; Lomotey & Deters, 2014) because it features strong reliability, data security, and minimum access-time latency. Figure 11 shows middleware's structure and its relation to OSI in detail.

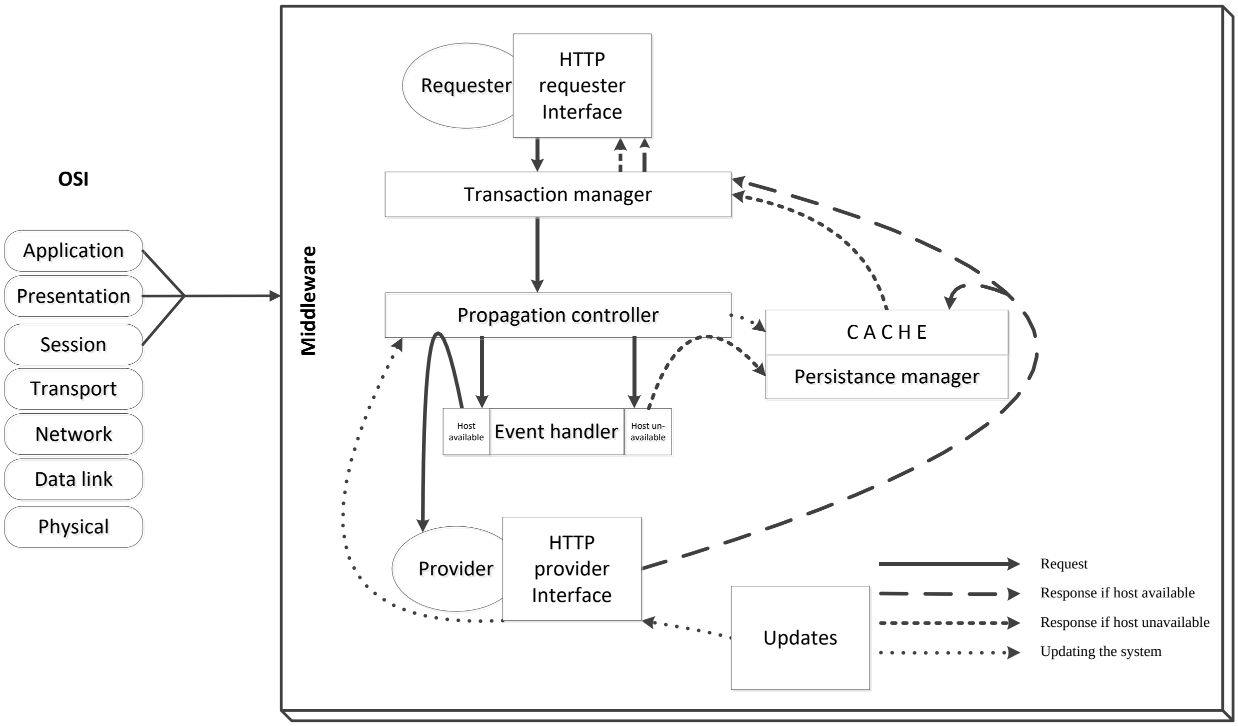


Figure 11. Middleware Structure and OSI Embedment (based on Tari & Bukhres, 2001; Lomotey et al., 2012)

mHealth not only bridges geographical distances between different healthcare stakeholders but also actively supports medical decision making processes. As Bellini et al. (2012) note: "Mobile devices and applications of Mobile Medicine have to provide a set of challenging features that cannot be met without the injection of a certain intelligence into the content itself". Thus, decision support systems often represent the centerpiece of mHealth applications.

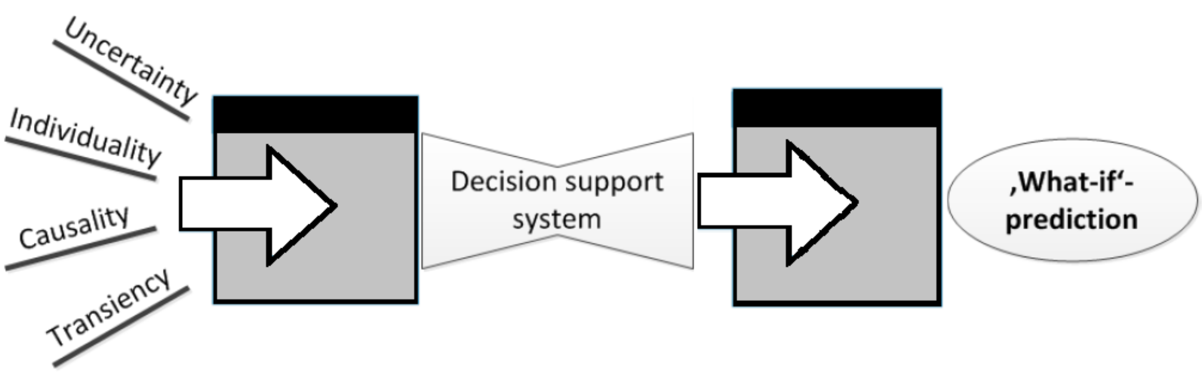


Figure 12. Principle of Medical Decision Support in Accordance with Hommersom et al. (2013)

As Figure 12 shows, these systems must understand the cause-effect relationships according to the current scientific state of knowledge without neglecting the uncertainty inherent to medical processes. Furthermore, medical decision support systems must be able to consider a patient's individual circumstances (personalization) and to provide "what-if" predictions. After all, the systems must also be capable of learning as medical processes often quickly change (Hommersom et al., 2013). A Bayesian network largely meets these complex requirements. Such a network represents a directed acyclic graph (DAG), which includes all known variables of a system as nodes and the statistical interactions between these variables as connecting lines. Probability tables describe the probability distribution of these variables, which depend on the status of so-called parent variables (Hommersom et al., 2013).

5 Discussion of Results and Implications for Future Research

5.1 mHealth: Impact and Critical Success Factors

As the name suggests, mHealth "is an emerging field in the intersection of medical informatics, public health and business, referring to health services and information delivered or enhanced through the Internet and related technologies" (Eysenbach, 2001). Through this synergy, we can overcome geographical distances between medical professionals and patients, medical professionals and their colleagues, and professionals/patients and medical databases. Simultaneously, we can use the computing power of mobile terminals and that of their connected central servers to solve medical problems concerning diagnosis, clinical communication, medical training, hospital information systems (HIS), self-healthcare management, assisted healthcare, supervised healthcare, and continuous monitoring (Chiarini et al., 2013; Mosa, Yoo, & Sheets, 2012).

Indeed, mHealth could lead to a quantum leap in medical data quality if one takes Nyquist's sampling theorem into consideration. Based on mathematical laws, the sampling frequency should be at least the double the highest signal frequency; in many examples such as a routine blood pressure (BP) measurement (circadian rhythm, typically with two peaks and two nadirs (Middeke, 2007); i.e., frequency = 2/day), we can easily recognize that clinical routine measurements (e.g., BP measurement only once or twice daily) do not provide sufficient reliability simply due to their low measurement frequency (Clifford & Clifton, 2012). In this context, mHealth provides the possibility for one to obtain the measurement frequency that one requires. Furthermore, one can use mHealth to build up a long-term medical record and to personalize healthcare (Clifford & Clifton, 2012). These characteristics of mHealth have led to a remarkable paradigm shift in medical care not only in high-technology countries but also in emerging and developing ones. In the lower-middle World Bank income group, the percentage of countries that report at least one mHealth initiative almost matches (~85%) the percentage for the high-income countries (World Health Organization, 2011). Examining mHealth economics shows benefits for clients/patients (e.g., increased medical effectiveness, increased access to healthcare, less work time missed, and reduced accommodation, meal, and transportation costs), providers (e.g., avoided inpatient visits, increased medication adherence, increased knowledge transfer among practitioners), and other stakeholders (e.g., increased productivity of workers due to less travel and less illness, avoided cases of communicable diseases). Thus, the economic potential of mHealth investments to reduce costs and increase efficiency becomes apparent from the perspective of all major health system stakeholders (Schweitzer & Synowiec, 2012).

Clinicians' acceptance and adoption represent the most critical success factors (CSF) to sustainably implement mHealth (Yu, Wu, Yu, & Xiao, 2006). One can best identify these future stakeholders' demands via diligent requirements engineering (Gerhardt et al., 2016). But, based on our own experience with modeling and implementing several major mHealth projects worldwide (Gerhardt et al., 2015; Gerhardt et al., 2016; Fellmann et al., 2011; Breitschwerdt et al. 2012; Metzger et al., 2017; Niemöller et al., 2016), we believe that one can only successfully establish the link between requirements engineering and marketable mHealth applications by using optimal technology in a context-sensitive manner. Gutiérrez-Ibarluzea, Chiumente, and Dauben (2017) have described the factors that influence the durability (lifecycle) of health technologies in detail. Because organizations in both the IT and healthcare sectors implement several of those influencing factors (e.g., research and development, investment options, spreading through clinical guidelines, speed of innovation) in a clearly pronounced way, mHealth technologies may have a shorter "durability" compared to technology in non-health related industries.

5.2 Scientific Contribution

Given the rapid technological progress (e.g., in sensor technology, wireless data transmission, data processing, and energy management) in highly divergent contexts that we continue to see today, information science needs to provide an adequate basis for future advancements. Our review contributes to that current scientific state of technology by first evaluating the relevant components of mHealth technology and then describing the current state of knowledge with respect to these components.

5.3 Component based mHealth Architecture Prototype

In Section 3, we systematically derive a component-based mHealth architecture prototype from the scientific literature (which included the AIS Senior Scholars' basket of journals). We identify several components that represent main mHealth system components: the portable device with internal and external (sensor) equipment, data transmission, interface, operating system, and embedded software application, internal and external memory, and power supply (see Figure 2).

5.4 From Hardware to Semantic Computing

With regard to these architectural components, we further searched leading technological and medical databases to review the current scientific knowledge of each of these components.

Concerning mobile devices/smartphones, we have seen increases in data transmission and computing speed, internal memory, internal sensor technology, and battery power in the last several years, which further improves the possibilities that mHealth will spread (see Table A1 in the Appendix). The communication between user and mHealth system has reached another milestone via semantic computing (Figure 10) and medical decision support systems (see Figure 12).

iOS and Android will likely prevail as the most dominant OS in the longer term; in comparing these two market leaders, we found that Android—as open source freeware—offers advantages in terms of flexibility and cost, while iOS has better safety aspects (see Table A4 in the Appendix). In addition, with regard to software integration, we show middleware's structure and its relation to OSI in detail in Section 4.6.2 (see Figure 11).

Obviously, mobile technologies require wireless data transmission; in this respect, the scientific literature unsurprisingly also deals with sensor-manager and cellular link technologies, which includes smartphone and sensor antenna design (see Figures 4 to 7), WBAN transceiver technology (see Table A2 in the Appendix), Wi-Fi/WiMAX features (Figure 3), and data-transmission architecture (see Figure 3).

With regard to the importance of external data storage, we also describe in detail the characteristics of cloud computing in accordance with NIST recommendations (Figure 9).

5.5 Main Focus: Sensor Technology

In analyzing the scientific literature, we focused on the diversity of available internal and external sensor technology in smartphones (additional equipment). Accordingly, we reflect that focus in this paper: we describe the relevant current sensor technologies in detail in Section 4.1.5. We were particularly impressed with the extent to which one can already use the standard features of contemporary high-end smartphones for mHealth purposes (see Figure 13).

5.6 "Combination" as a Key Concept of mHealth Wireless Link Technology

After evaluating the scientific mHealth technology literature, we believe that "combination" represents a key concept of mHealth engineering. As an example, we address the wireless link technologies: we show that WiMAX is technologically superior to 3G and offers an attractive range up to 50 km. On the other hand, Wi-Fi has a very low range but significantly surpasses WiMAX in terms of data-transfer velocity. However, combining these two technologies by using WiMAX to link up Wi-Fi hotspots results in an excellent hybrid technology (Song & Isaac, 2014). Another examples involves combining BT-LE and RFID technology: BT-LE is an excellent and widespread sensor-manager link technology for simultaneously processing multiple medical devices. It has a long wireless range, a high data-transmission rate, a long battery life, and follows CoAP standards. However, Bluetooth technology's main disadvantage concerns its long-winded pairing procedure. Passive RFID can compensate for this disadvantage by rapidly delivering Bluetooth pairing information.

5.7 Implications for Future Research

Finally, our review also provides notes on unresolved issues in applying mHealth, such as with regard to data-protection issues, potential bottlenecks in the energy supply (see Table A1 in the Appendix and Figure 7) of sensors and mobile terminals in developing countries, and mHealth data processing and storage (see Table 4).

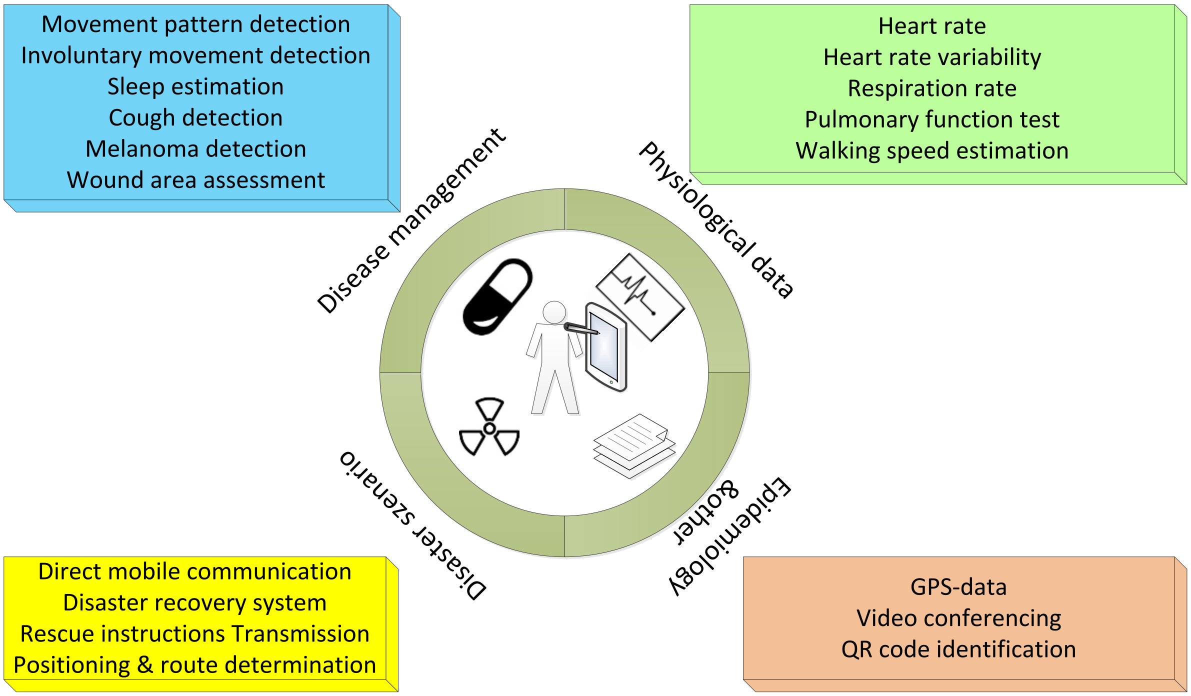


Figure 13. mHealth Technology on the Basis of Smartphone Standard Equipment

Acknowledgments

We thank the *JITTA* reviewers and the AIS copyeditor for their valuable comments. In addition, we thank Jan vom Brocke for his critical review of the manuscript and his advice. The present review forms part of the first author's PhD thesis. He described the appropriate research process, performed the literature review and analyzed mHealth keywords, developed the prototypical component-based mHealth architecture, described the individual components, and contributed decisively to the discussion. The other two authors acted as scientific supervisors, supplemented the literature selection with respect to the AIS Senior Scholar's basket of journals, and revised the manuscript. All authors declare that no conflicts of interest exist.

References

3GPP. (2018a). *Drafting and publication of GSM Specs in the pre-3GPP era*. Retrieved from http://www.3gpp.org/specifications/gsm-history

3GPP. (2018b). *LTE*. Retrieved from http://www.3gpp.org/technologies/keywords-acronyms/98-lte

Abu-Faraj, Z. O., Chaleby, M. H., Barakat, S. S., & Zaklit, J. D. (2011). A SIM card-based ubiquitous medical record bracelet/pendant system—a pilot study. In *Proceedings of the 4th International Conference on Biomedical Engineering and Informatics* (pp.1914-1918).

Adibi, S. (2012). Link technologies and blackberry mobile health (mHealth) solutions: A review. *IEEE Transactions on Information Technology in Biomedicine*, *16*(4), 586-597.

Adibi, S. (2013). Mobile health (mHealth) biomedical imaging paradigm. In *Proceedings of the 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 6453-6457).

Adibi, S. (2015). A mobile health network disaster management system. In *Proceedings of the 7th International Conference on Ubiquitous and Future Networks* (pp. 424-428).

Agu, E., Pedersen, P., Strong, D., Tulu, B., He, Q., Wang, L., & Li, Y. (2013). The smartphone as a medical device: Assessing enablers, benefits and challenges. In *Proceedings of the IEEE International Workshop of Internet-of-Things Networking and Control* (pp. 48-52).

Al-Dowaihi, D., Al-Ajlan, M., Al-Zahrani, N., Al-Quwayfili, N., Al-Jwiser, N., & Kanjo, E. (2013). Mbreath: Asthma monitoring system on the go. In *Proceedings of the International Conference on Computer Medical Applications.*

Ali, E. E., Chew, L., & Yap, K. Y.-L. (2016). Evolution and current status of mhealth research: A systematic review. *BMJ Innovation*, *2*, 33-40.

Altin, M., Vullers, R., Van Hoof, C., van Dort, M., & Amft, O. (2014). Self-calibration of walking speed estimations using smartphone sensors. In *Proceedings of the IEEE International Conference on Pervasive Computing and Communications Workshops* (pp. 10-18).

Aranda-Jan, C. B., Mohutsiwa-Dibe, N., & Loukanova S. (2014). Systematic review on what works, what does not work and why of implementation of mobile health (mHealth) projects in Africa. *BMC Public Health*, *14*(188), 1-15.

AreaDigital. (n.d.). *Handy bestenliste—die besten handys im überblick.* Retrieved from http://www.areamobile.de/bestenlisten/highend-handys

Atmel Corporation. (2014). *Example of battery lifetime for ATA6286C active RFID transceiver*. Retrieved from http://ww1.microchip.com/downloads/en/AppNotes/Atmel-9367-Example-of-Battery-Lifetime-for-ATA6286C_Application-Note.pdf

Attard, S., & Zammit, S. (2013). Effect of human movement on the body coupled communications channel in body area networks. In *Proceedings of the IEEE International Conference on Smart Technologies* (pp. 335-339).

Azfar, A., Choo, K.-K. R., & Liu, L. (2015). Forensic taxonomy of popular Android mHealth apps. In *Proceedings of 21st Americas Conference on Information Systems* (pp. 1-19).

Balsam, J., Bruck, H. A., & Rasooly, A. (2013). Orthographic projection capillary array fluorescent sensor for mHealth. *Methods*, *63*(3), 276-281.

Beer, W. (2004). Definition of terms. *Smartlab*. Retrieved from http://www.smartlab.at/proceedings/phd-thesis-context- awareness/chapter-1/

Behar, J., Roebuck, A., Shahid, M., Daly, J., Hallack, A., Palmius, N., Stradling, J., & Clifford, G. D. (2015). SleepAp: An automated obstructive sleep apnoea screening application for smartphones. *IEEE Journal of Biomedical and Health Informatics*, *19*(1), 325-331.

Bellini, P., Bruno, I., Cenni, D., Fuzier, A., Nesi, P., & Paolucci, M. (2012). Mobile medicine: Semantic computing management for health care applications on desktop and mobile devices. *Multimediea Tools and Applications*, *58*(1), 41-79.

Boonchieng, E., Boonchieng, W., Senaratana, W., & Singkaew, J. (2014). Development of mHealth for public health information collection, with GIS, using private cloud: A case study of Saraphi district, Chiang Mai, Thailand. In *Proceedings of the International Computer Science and Engineering Conference* (pp. 350-353).

Borodin, A., Zavyalova, Y., Zaharov, A., & Yamushev, I. (2015). Architectural approach to the multisource health monitoring application design. In *Proceedings of the 17th Conference of Open Innovations Association* (pp.16-21).

Breitschwerdt, R., Reinke, P., Kleine Sextro, M., & Thomas, O. (2012). Process-oriented application systems for mobile services: Empirical analysis of healthcare professionals' intention. *ACM SIGHIT Record*, *2*(2), 22-30.

Brown, W., Ibitoye, M., Bakken, S., Schnall, R., Balán, I., Frasca, T., & Carballo-Diéguez, A. (2015). Cartographic analysis of antennas and towers: A novel approach to improving the implementation and data transmission of mHealth tools on mobile networks. *JMIR mHealth uHealth*, *3*(2), e63.

Buntin, M. B., Burke, M. F., Hoaglin, M. C., & Blumenthal D. (2011). The benefits of health information technology: A review of the recent literature shows predominantly positive results. *Health Affairs*, *30*(3), 464-471

Byrne, E., Manada, A., Marinkovic, S., & Popovici, E. (2011). A graph theoretical approach for network coding in wireless body area networks. In *Proceedings of the IEEE International Symposium on Information Theory* (pp. 405-409).

Carspecken, C. W., Arteta, C., & Clifford, G. D. (2013). TeleSpiro: A low-cost mobile spirometer for resource-limited settings. In *Proceedings of the IEEE Point-of-Care Healthcare Technologies* (pp. 144-147).

Cecere, G., Corrocher, N., & Battaglia, R. D. (2015). Innovation and competition in the smartphone industry. *Telecommunications Policy*, *39*(3), 162-175.

Chen, H.-M., Liou, Y.-Z., Chen, S.-Y., & Li, J.-S. (2013a). Design of mobile healthcare service with health records format evaluation. In *Proceedings of the IEEE 17th International Symposium on Consumer Electronics* (pp. 257-258).

Chen, N.-C., Wang, K.-C., & Chu, H.-H. (2012). Listen-to-nose: A low-cost system to record nasal symptoms in daily life. In *Proceedings of the ACM Conference on Ubiquitous Computing* (pp. 590-591).

Chen, Z., Lin, M., Chen, F., Lane, N. D., Cardone, G., Wang, R., Li, T., Chen, Y., Choudhury, T., & Campbell, A. T. (2013b). Unobtrusive sleep monitoring using smartphones. In *Proceedings of the 7th International Conference on Pervasive Computing Technologies for Healthcare* (pp. 145-152).

Chiarini, G., Ray, P., Akter, S., Masella, C., & Ganz, A. (2013). mHealth technologies for chronic diseases and elders: A systematic review. *IEEE Journal on Selected Areas in Communications*, *31*(9), 6-18.

Chigona, W., Nyemba, M., & Metfula, A. (2012). A review on mHealth research in developing countries. *The Journal of Community Informatics*, *9*(2). Retrieved from http://ci-journal.net/index.php/ciej/article/view/941/1011

Clifford, G. D., & Clifton D. (2012). Wireless technology in disease management and medicine. *Annual Review of Medicine*, *63*(1), 479-492.

Crema, C., Depari, A., Flammini, A., Lavarini, M., Sisinni, E., & Vezzoli, A. (2015). A smartphone-enhanced pill-dispenser providing patient identification and in-take recognition. In *Proceedings of the IEEE International Symposium on Medical Measurements and Applications* (pp. 484-489).

Crossbowtechnology. (2003). MTS—sensor, data acquisition boards. Retrieved from http://cseweb.ucsd.edu/groups/csag/html/teaching/cse291s03/OtherCourseMaterial/Crossbow/MTS-MDA_Series_User_Manual.pdf

DeRidder, M., Kim, J., Jing, Y., Khadra, M., & Nanan, R. (2015). A systematic review on incentive-driven mobile health technology: As used in diabetes management. *Journal of Telemedicine and Telecare,* *23*(1), 26-35.

Dinh, H. T., Lee, C., Niyato, D., & Wang, P. (2013). A survey of mobile cloud computing: Architecture, applications, and approaches. *Wireless Communications and Mobile Computing*, 13(18), 1587-1611.

Duarte, J. M. G., Yokoyama, R. S., & Villas, L. A. (2015). A low cost mHealth non-intrusive method to monitoring patient indoor Localization. *IEEE Latin America Transactions*, *13*(8), 2668-2673.

Dumanli, S., Gormus, S., & Craddock, I. J. (2012). Energy efficient body area networking for mHealth applications. In *Proceedings of the International Symposium on Medical Information and Communication Technology* (pp. 1-4).

Dunsmuir, D. T., Payne, B. A., Cloete, G., Petersen, C. L., Görges, M., Lim, J., von Dadelszen, P., Dumont, G. A., & Ansermino, J. M. (2014). Development of mHealth applications for pre-eclampsia triage. *Journal of Biomedical and Health Informatics*, *18*(6), 1857-1864.

Duregger, K., Hayn, D., Morak, J., Ladenstein, R., & Schreier, G. (2015). An mHealth system for toxicity monitoring of paediatric oncological patients using near field communication technology. In *Proceedings of the 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 6848-6851).

Ertin, E., Stohs, N., Kumar, S., Raij, A., al'Absi, M., Shah, S., Mitra, S., Kwon, T., & Jeong, J. W. (2011). AutoSense: Unobtrusively wearable sensor suite for inferring the onset, causality, and consequences of stress in the field. In *Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems* (pp. 274-287).

Eskenazi, B., Quirós-Alcalá, L., Lipsitt, J. M., Wu, L. D., Kruger, P., Ntimbane, T., Nawn, J. B., Bornman, M. S., & Seto, E. (2014). mSpray: A mobile phone technology to improve malaria control efforts and monitor human exposure to malaria control pesticides in Limpopo, South Africa. *Environmental International*, *68*, 219-226.

Etemadi, M., Inan, O. T., Heller, J. A., Hersek, S., Klein, L., & Roy, S. (2016). A wearable patch to enable long-term monitoring of environmental, activity and hemodynamics variables*. IEEE Transactions on Biomedical Circuits and Systems*, *10*(2), 280-288.

Eysenbach, G. (2001). What is e-health? *Journal of Medical Internet Research*, *3*(2), e20.

Fellmann, M., Hucke, S., Breitschwerdt, R., Thomas, O., Blinn, N., & Schlicker, M. (2011). Informationssystemarchitekturen zur Unterstützung technischer Kundendienstleistungen. In *Proceedings of the 10th International Conference on Wirtschaftsinformatik* (pp. 252-261).

Free, C., Phillips, G., Felix, L., Galli, L., Patel, V., & Edwards, P. (2010). The effectiveness of M-health technologies for improving health and health services: A systematic review protocol. *BMC Research Notes, 3*(250).

Free, C., Phillips, G., Watson, L., Galli, L., & Felix, L. (2013). The effectiveness of mobile-health technologies to improve health care service delivery processes: A systematic review and meta-analysis. PLoS Med, *10*(1), e1001363.

Gakare, P. K., Patel, A. M., Vaghela, J. R., Awale, R. N. (2012). Real time feature extraction of ECG signal on android platform. In *Proceedings of the International Conference on Communication, Information & Computing Technology* (pp. 1-5).

Gartner. (2016). *Gartner says worldwide smartphone sales grew 9.7 Percent in fourth quarter of 2015.* Retrieved from http://www.gartner.com/newsroom/id/3215217

Gehlot, N. S. (2012). State-of-the-art of mobile-health: Technology, sensors and clinical applications. *Revista de Tecnologia da Informacao e Comunicacao*, *2*(1), 20-24.

Gerhardt, U., Breitschwerdt, R., & Thomas, O. (2015). Relapse prevention in drug addiction: Addressing a messy problem by IS Action Research. *AI & Society*, *30*(1), 31-43.

Gerhardt, U., Breitschwerdt, R., & Thomas, O. (2016a). Engineering sustainable mHealth: The role of action research. *AI & Society*, *32*(3), 339-357.

Gerhardt, U., Hindermann, V., & Kiesow, A. (2016b). Von der Analyse zum design: Entwicklung eines mHealth-systems als individualisierte behandlungsform zur rückfallprophylaxe bei drogenabhängigkeit. *Tagungsband Multikonferenz Wirtschaftsinformatik* (pp. 643- 654).

Ghazal, M., Al Khalil, Y., Dehbozorgi, F. J., & Alhalabi, M. T. (2015). An integrated caregiver-focused mHealth framework for elderly care. In *Proceedings of the 11th IEEE International Conference on Wireless and Mobile Computing, Networking and Communications* (pp. 238-245).

Gutiérrez-Ibarluzea, I., Chiumente, M., Dauben, H. P. (2017). The life cycle of health technologies: Challenges and ways forward. *Frontiers in Pharmacol*ogy, 8(14).

Hall, A. K., Cole-Lewis, H., & Bernhardt, J. M. (2015). Mobile text messaging for health: A systematic review of reviews. *Annual Review of Public Health*, *36*, 393- 415.

Hasida, K. (2007). Semantic authoring and semantic computing. *In Proceedings of the Annual Conference of the Japanese Society for Artificial Intelligence* (LNCS vol. 3609, pp. 137-149).

Hayn, D., Jammerbund, B., & Schreier, G. (2011). ECG quality assessment for patient empowerment in mHealth applications. In *Proceedings on the Computing in Cardiology* (pp. 353-356).

Hertz, H. (1892). *Untersuchungen ueber die ausbreitung der elektrischen kraft*. Leipzig: Johann Ambrosius Barth.

Hommersom, A., Lucas, P. J. F., Velikova, M., Dal, G., Bastos, J., Rodriguez, J., Germs, M., & Schwietert, H. (2013). MoSHCA—my mobile and smart health care assistant. In *Proceedings of the IEEE 15th International Conference on e-Health Networking, Applications & Services* (pp. 188-192).

Huang, A., Xu, W., Li, Z., Xie, L., Sarrafzadeh, M., Li, X., & Cong, J. (2014). System light-loading technology for mHealth: Manifold-learning-based medical data cleansing and clinical trials in WE-CARE project. *Journal of Biomedical and Health Informatics*, *18*(5), 1581-1589.

Islam T. (n.d.). BTS, GSM & 3G Services & network overview of Grameenphone Bangladesh LTD. *East West University.* Retrieved from http://dspace.ewubd.edu/bitstream/handle/123456789/1804/Tanjil_Islam.pdf?sequence=1&isAllowed=y

Jacinto, N. (2009). *Performance gains evaluation from UMTS/HSPA+ to LTE at the radio network level* (master's thesis). Technical University of Lisbon, Lisbon, Portugal.

Jara, A. J., Zamora-Izquierdo, M. A., & Skarmeta, A. F. (2012). Knowledge acquisition and management architecture for mobile and personal health environments based on the Internet of things. In *Proceedings of the 11th International Conference on Trust, Security and Privacy in Computing and Communications* (pp. 1811-1818).

Jara, A. J., Zamora-Izquierdo, M. A., & Skarmeta, A. F. (2013). Interconnection framework for mhealth and remote monitoring based on the Internet of things. *Journal on Selected Areas in Communications*, *31*(9), 47-65.

Joshi, V., Holtzman, M., Arcelus, A., Goubran, R., & Knoefel, F. (2012). Highly survivable bed pressure mat remote patient monitoring system for mHealth. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 268- 271).

Jovanov, E., Milosevic, M., & Milenkovic, A. (2013). A mobile system for assessment of physiological response to posture transitions. In *Proceedings of the 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 7205-7208).

Kartsakli, E., Lalos, A. S., Antonopoulos, A., Tennina, S., Renzo, M. D., Alonso, L., & Verikoukis, C. (2014). A survey on M2M systems for mHealth: A wireless communications perspective. *Sensors*, *14*(10), 18009-52.

Kazantsev, A. P., Senin, A. A., Ponomareva, J. N., & Mochalova, M. N. (2014). An mHealth approach to remote fetal monitoring. In *Proceedings of the Healthcare Innovation Conference* (pp. 239-242).

Khorakhun, C., & Bhatti, S. N. (2014). Using online social media platforms for ubiquitous, personal health monitoring. In *Proceedings of the 16th International Conference on e-Health Networking, Applications and Services* (pp. 287-292).

Kibret, B., Teshome, A. K., Lai, D. T. H. (2014). Human body as antenna and its effect on human body communications. *Progress in Electromagnetics Research*, *148*, 193-207.

Kwak, K. S., Ullah, S., & Ullah, N. (2010). An overview of IEEE 802.15.6 standard. In *Proceedings of the 3rd International Symposium on Applied Sciences in Biomedical and Communication Technologies.*

Kyriacou, E. C., Pattichis, C. S., & Pattichis, M. S. (2009). An overview of recent health care support systems for eEmergency and mHealth applications. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 1246-1249).

Larson, E. C., Goel, M., Redfield, M., Boriello, G., Rosenfeld, M., & Patel, S. N. (2013). Tracking lung function on any phone. In *Proceedings of the 3rd ACM Symposium on Computing for Development.*

Larson, E. C., Lee, T., Liu, S., Rosenfeld, M., & Patel, S. N. (2011). Accurate and privacy preserving cough sensing using a low-cost microphone. In *Proceedings of the 13th International Conference on Ubiquitous Computing* (pp. 375-384).

Lehr, W., & McKnight, L. W. (2003). Wireless Internet access: 3G vs. WiFi? *Telecommunications Policy*, *27*, 351-370.

Lennon, T., Bernier, T., Tamayo, D., Goldberg, C., & Mankodiya, K. (2015). Multi-sensory system for monitoring dyskinesia in movement disorders. In *Proceedings of the 41st Annual Northeast Biomedical Engineering Conference.*

Li, Z., Huang, A., Xu, W., Hu, W., & Xie, L. (2014). Fall perception for elderly care: A fall detection algorithm in smart wristlet mHealth system. In *Proceedings of the IEEE International Conference on Communications* (pp. 4270-4274).

Liu, B., Wang, D., Li, S., Nie, X., Xu, S., Jiao, B., Duan, X., & Huang, A. (2015). Design and implementation of an intelligent belt system using accelerometer. In *Proceedings of the 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 2043-2046).

Liu, Y., Wu, M., & Hou, H. (2012). The design and implement of mobile heath management software base on the Android platform. In *Proceedings of the International Symposium on Information Science and Engineering* (pp. 307-310).

Lomotey, R. K., & Deters, R. (2014). Mobile-based medical data accessibility in mHealth. In *Proceedings of the 2nd IEEE International Conference on Mobile Cloud Computing, Services, and Engineering* (pp. 91-100).

Lomotey, R. K., Jamal, S., & Deters, R. (2012). SOPHRA: A mobile web services hosting infrastructure in mHealth. In *Proceedings of the IEEE First International Conference on Mobile Services* (pp. 88-95).

Luxton, D. D., June, J. D., & Chalker, S. A. (2015). Mobile health technologies for suicide prevention: Feature review and recommendations for use in clinical care. *Current Treatment Options in Psychiatry*, 2(4), 3490362.

Ma, L., & Jia, D. (2005). The competition and cooperation of WiMAX, WLAN and 3G. In *Proceedings of the 2nd International Conference on Mobile Technology, Applications and Systems*.

Marinkovic, S., & Popovici, E. (2012). Ultra low power signal oriented approach for wireless health monitoring. *Sensors*, *12*(6), 7917-37.

Matthew-Maich, N., Harris, L., Ploeg, J., Markle-Reid, M., Valaitis, R., Ibrahim, S., Gafni, A., & Isaacs, S. (2016). Designing, implementing, and evaluating mobile health technologies for managing chronic conditions in older adults: A scoping review. *JMIR Mhealth Uhealth*, *4*(2), e29.

Mazloum, N. S. (2008). *Body-coupled communications—experimental characterization, channel modeling and physical layer design* (master’s thesis). Department of Signals and Systems Distributed Sensor Systems, Chalmers University of Technology.

Mell, P., & Grance, T. (2011). *The NIST definition of cloud computing—recommendations of the National Institute of Standards and Technology* (special publication 800-145). U.S. Department of Commerce.

Metzger, D., Niemöller, C., & Thomas, O. (2017). Design and demonstration of an engineering method for service support systems. *Information Systems and e-Business Management*, *2017*(4), 1-35.

Michailidis, C., Smanis, I., Stamatis, K., Bergeles, C., & Kouris, A. (2014). Development of a smartphone-enabled spirometer for personalised respiratory health. In *Proceedings of the 4th International Conference on Wireless Mobile Communication and Healthcare* (pp. 67-70).

Middeke, M. (2007). Hypertonie—chronopathologie und chronotherapie. *Kompendium Herz-Kreislauf*, *3*(1), 17-22.

Morak, J., Schwarz, M., Hayn, D., & Schreier, G. (2012). Feasibility of mHealth and near field communication technology based medication adherence monitoring. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 272-275).

Mosa, A. S. M., Yoo, I., & Sheets, L. (2012). A systematic review of healthcare applications for smartphones. *BMC Medical Informatics and Decision Making*, *12*(67).

Movassaghi, S., Abolhasan, M., Lipman, J., Smith, D., & Jamalipour, A. (2014). Wireless body area networks: A survey. *IEEE Communications Surveys & Tutorials*, *16*(3), 1658-1686.

Navarro, K. F., Lawrence, E., & Lim. B. (2009). Medical MoteCare: A distributed personal healthcare monitoring system. In *Proceedings of the International Conference on eHealth, Telemedicine and Social Medicine* (pp. 25-30).

Niemöller. C., Metzger. D., Berkemeier. L., Zobel. B., Thomas, O., & Thomas, V. (2016). Designing mHealth applications for developing countries. In *Proceedings of the European Conference on Information Systems.*

Odendaal, W. A., Goudge, J., Griffiths, F., Tomlinson, M., Leon, N., & Daniels, K. (2015). Healthcare workers' perceptions and experience on using mHealth technologies to deliver primary healthcare services: Qualitative evidence synthesis. *Cochrane Database of Systematic Reviews*. Retrieved from https://www.cochranelibrary.com/cdsr/doi/10.1002/14651858.CD011942/epdf/full

Oster, J., Behar, J., Colloca, R., Li, Q., Li, Q., & Clifford, G. D. (2013). Open source Java-based ECG analysis software and Android app for atrial fibrillation screening. In *Proceedings of the Computing in Cardiology Conference* (pp. 731-734).

Pimentel, M. A. F., Santos, M. D., Arteta, C., Domingos, J. S., Maraci, M. A., Clifford, G. D. (2014). Respiratory rate estimation from the oscillometric waveform obtained from a non-invasive cuff-based blood pressure device. In *Proceedings of the 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 3821-3824).

Poh, M.-Z., Kim, K., Goessling, A., Swenson, N., & Picard, R. (2012). Cardiovascular monitoring using earphones and a mobile device. *IEEE Pervasive Computing*, *11*(4), 18-26.

Poh, M.-Z., McDuff, D. J., & Picard, R. W. (2011). Advancements in noncontact, multiparameter physiological measurements using a webcam. *IEEE Transactions on Biomedical Engineering*, 58(1), 7-11.

Poon, T. W. K., & Friesen, M. R. (2015). Algorithms for size and color detection of smartphone images of chronic wounds for healthcare applications. *IEEE Access*, *3*, 1799-1808.

Postolache, O., Girao, P. S., Ribeiro, M., Guerra, M., Pincho, J., Santiago, F., & Pena, A. (2011). Enabling telecare assessment with pervasive sensing and Android OS smartphone. In *Proceedings of the IEEE International Workshop on Medical Measurements and Applications* (pp. 288-29).

Raman, A. (n.d.). Mobile operating system—a comparative study of Mobile OS. *A Tech Journey.* Retrieved from http://atechjourney.com/mobile-operating-system-a-comparative-study-of-mobile-os.html/

Rebolledo-Nandi, Z., Chávez-Olivera, A., Cuevas-Valencia, R. E., Alarcón-Paredes, A., & Alonso, G. A. (2015). Design of a versatile low cost mobile health care monitoring system using an android application. In *Proceedings of the Pan American Health Care Exchanges*.

Research 2 Guidance. (2015). *mHealth app developer economics 2015.* Retrieved from https://research2guidance.com/product/mhealth-developer-economics-2015/

Saleheen, N., Ali, A. A., Hossain, S. M., Sarker, H., Chatterjee, S., Marlin, B., Ertin, E., Al'Absi, M., & Kumar. S. (2015). puffMarker: A multi-sensor approach for pinpointing the timing of first lapse in smoking cessation. In *Proceedings of the ACM International Conference on Ubiquitous Computing* (pp. 999-1010).

Sannino, G., De Falco, I., & De Pietro, G. (2014). An automatic rules extraction approach to support OSA events detection in an mHealth system. *IEEE Journal of Biomedical and Health Informatics*, *18*(5), 1518-1524.

Santos, D. F. S., Almeida, H. O., & Perkusich, A. (2015). A personal connected health system for the Internet of things based on the constrained application protocol. *Computers and Electrical Engineering*, *44*, 122-136.

Sax, C., & Lawrence, E. (2009). Point-of-treatment: Touchable e-nursing user interface for medical emergencies. In *Proceedings of the 3rd International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies* (pp. 89-95).

Schweitzer, J., & Synowiec, C. (2012). The economics of eHealth and mHealth. *Journal of Health Communication: International Perspectives*, *17*(1), 73-81.

Secerbegovic, A., Mujcic, A., Suljanovic, N., Nurkic, M., & Tasic, J. (2011). The research mHealth platform for ECG monitoring. In *Proceedings of the 11th International Conference on Telecommunications* (pp. 103-108).

Sharma, R. (n.d.). Low-energy wireless. *NXP.* Retrieved from http://cache.freescale.com/files/microcontrollers/doc/brochure/LowEnergyWireless.pdf

Shi, R., Chen, Z., Wang, H., Sun, P., Trull, T., & Shang, Y. (2015). mAAS—a mobile ambulatory assessment system for alcohol craving studies. In *Proceedings of the 39th Annual Computer Software and Applications Conference* (pp. 282-287).

Smiley, S. (2016). Active RFID vs. passive RFID: What's the difference? *RFID Insider*. Retrieved from http://blog.atlasrfidstore.com/active-rfid-vs-passive-rfid

Song, S., & Issac, B. (2014). Analysis of WiFi and QiMAX and wireless network coexistence. *International Journal of Computer Networks & Communications*, *6*(6), 63-78.

Song, W. (2011). Heterogeneous multi-hop transmission of compressed ECG data from wireless body area network. In *Proceedings of the International Conference on Communications*.

Steute Schaltgeräte. (2010). *Das Funkbuch*. Löhne: Westfalia Druckerei.

Tari, Z., & Bukhres, O. (2001). *Fundamentals of distributed object systems: The CORBA perspective*. New York, NY: John Wiley & Sons.

Turner, J. E., Jessup, M. S., & Tong, K.-F. (2012). A novel technique enabling the realisation of 60 Ghz body area networks. In *Proceedings of the 9th International Conference on Wearable and Implantable Body Sensor Networks* (pp. 58-62).

U.S. National Library of Medicine. (2016). *Unified medical language system*. Retrieved from https://www.nlm.nih.gov/research/umls/quickstart.html

Varshney, U. (2007). Pervasive healthcare and wireless health monitoring. *Journal on Mobile Networks and Applications*, *12*(2-3), 113-127.

Vazquez-Briseno, M., Navarro-Cota, C., Nieto-Hipolito, J. I., Jimenez-Garcia, E., & Sanchez-Lopez, J. D. (2012). A proposal for using the Internet of things concept to increase children's health awareness. In *Proceedings of the 22nd International Conference on Electrical Communications and Computers* (pp. 168-172).

Wadhawan, T., Ning, S., Hu, R., Lancaster, K., Xiaojing, Y., & Zouridakis, G. (2011). Implementation of the 7-point checklist for melanoma detection on smart handheld devices. In *Proceedings of the IEEE Engineering in Medicine and Biology Society* (pp. 3180-3183).

Wait, J. R. (1957). Excitation of surface waves on conducting, stratified, dielectric-clad, and corrugated surfaces. *Journal of Research of the National Bureau of Standards*, *59*(6), 365-377.

Wang, L., Pedersen, P. C., Strong, D. M., Tulu, B., Agu, E., & Ignotz, R. (2015). Smartphone-based wound assessment system for patients with diabetes. *IEEE Transactions on Biomedical Engineering*, *62*(2), 477-488.

Wannstrom, J. (2018). HSPA. *3GPP.* Retrieved from http://www.3gpp.org/technologies/keywords-acronyms/99-hspa

Watanabe, H., Kawarasaki, M., Sato, A., & Yoshida, K. (2012). Development of wearable heart disease monitoring and alerting system associated with smartphone. In *Procedings of the 14th International Conference on e-Health Networking, Applications and Services* (pp. 292-297).

White, P. J. F., Podaima, B. W., & Friesen, M. R. (2014). Algorithms for smartphone and tablet image analysis for healthcare applications. *IEEE Access*, *2*, 831-840.

Wimmer, F. (2015). Alternative mobile operating systems in comparison. *Notebook Check*. Retrieved from https://www.notebookcheck.net/Alternative-Mobile-Operating-Systems-in-Comparison.137283.0.html

World Health Organization. (2011). mHealth—new horizons for health through mobile technologies. Retrieved from http://www.who.int/goe/publications/goe_mhealth_web.pdf

Wukkadada, B., Nambiar, R., & Nair, A. (2015). Mobile operating system: Analysis and comparison of Android and iOS. *International Journal of Computing and Technology*, *2*(7), 273-276.

Würstl, D. (2016). *Vergleich Entwicklungsumgebungen für die app Programmierung.* Retrieved from http://www.app-entwickler-verzeichnis.de/faq-app-entwicklung/10-app-programmierung/32-vergleich-entwicklungsumgebungen-fuer-die-app-programmierung

Wuryandari, A. I., & Suprijono, H. (2012). Design and implementation of blood pressure measuring and oximetry (Android based). In *Proceedings of the International Conference on System Engineering and Technology.*

Yang, L., Ge, Y., Li, W., Rao, W., & Shen, W. (2014). A home mobile healthcare system for wheelchair users. In *Proceedings of the IEEE 18th International Conference on Computer Supported Cooperative Work in Design* (pp. 609-614).

Yao, C., Sun, A., & Hall, D. A. (2015). Efficient power harvesting from the mobile phone audio jack for mHealth peripherals. In *Proceedings of the IEEE Global Humanitarian Technology Conference* (pp. 219-225).

Yu, P., Wu, M. X., Yu, H., & Xiao, G. Q. (2006). The challenges for the adoption of m-health. In *Proceedings of the IEEE International Conference on Service Operations and Logistics and Informatics* (pp. 181-186).

Yusufov, M., Paramonov, I., & Timofeev, I. (2013). Medicine tracker for smart TV. In *Proceedings of the 14th Conference of Open Innovations Association* (pp. 164-170).

Zendesk (2018). *Mobile device compatibility (tablet/smartphone) with ANT+ or Bluetooth Smart*. Retrieved from https://elitesrl.zendesk.com/hc/en-us/articles/115004148729-Mobile-device-compatibility-tablet-smartphone-with-ANT-or-Bluetooth-Smart?mobile_site=true

Zhang, W., Passow, P., Jovanov, E., Stoll, R., & Thurow, K. (2013). A secure and scalable telemonitoring system using ultra-low-energy wireless sensor interface for long-term monitoring in life science applications. In *Proceedings of the IEEE International Conference on Automation Science and Engineering* (pp. 617-622).

Zhu, T., Wang, L., & Meng, J. (2013). The exploitation and discussion of new mobile healthcare system model based on smart phone. In *Proceedings of the 10th IEEE International Conference on Networking, Sensing and Control* (pp. 497-502).

Appendix A: Technical Tables

Table A1. Comparison Chart: Technical Data of Current High-end Smartphones (in accordance with AreaDigital, 2016)

	Samsung Galaxy S7 Edge	HTC 10	Huawei P9	LG G5	Apple iPhone 6S Plus
OS	Android 6.0 Marshmallow	Android 6.0 Marshmallow	Android 6.0 Marshmallow	Android 6.0 Marshmallow	iOS 9
CPU	2.3 GHz	2.15 GHz	2.5 GHz	2.1 GHz	1.8 GHz
GPU	Mali-T880	Adreno 530	Mali-T880 MP4	Adreno 530	PowerVR GT7600
RAM	4 GB	4 GB	3 GB	4 GB	2 GB
Memory (max expansion)	32 GB (200 GB)	32 GB (200 GB)	32 GB (128 GB)	32 GB (2000 GB)	128 GB
Data protocol	HSDPA, HSUPA, LTE	HSDPA, HSUPA, LTE	HSDPA, HSUPA, LTE	HSDPA, HSUPA, LTE	HSDPA, HSUPA, LTE
Data rate	450 Mbps	450 Mbps	300 Mbps	300 Mbps	300 Mbps
Bluetooth	4.2	4.2	4.2	4.2	4.2
Wi-Fi	802.11ac/b/g/n	802.11ac/b/g/n	802.11ac/b/g/n	802.11ac/b/g/n	802.11ac/b/g/n
GPS	Yes (+ GLONASS)	Yes (+ GLONASS)	Yes (+ GLONASS)	Yes (+ GLONASS)	Yes (+ GLONASS)
NFC	Yes	Yes	Yes	Yes	Yes
Sensors	ACC,CMP,FPS,GYR, PRX,ALS	ACC,CMP,FPS,GYR, PRX,ALS	ACC,FPS,GYR, PRX,ALS	ACC,CMP, FPS,GYR, PRX,ALS	BAR, ACC,CMP,FPS, GYR, PRX,ALS
Battery	3600 mAh	3000 mAh	3000 mAh	2800 mAh	2750 mAh

Legend: OS: operating system, CPU: central processing unit, GPU: graphics processing unit, RAM: random-access memory, GPS: global positioning system, NFC: near field communication, BAR: barometer, ACC: accelerometer, CMP: digital compass (magnetometer), FPS: fingerprint sensor, GYR: gyroscope PRX, proximity sensor, ALS: ambient light sensor.

Table A2. Description of the WBAN Transceiver Standards in Accordance with IEEE 802.15.6 (Kwak et al. 2010; Kartsakli et al., 2014; Kibret, Teshome, & Lai, 2014)

WBAN transceiver technology	Description
Narrowband (NB)	Initially used in short- and medium-range wireless data transmission (ZigBee, Bluetooth, WLAN). In WBAN context, these receiver/transmitter systems operate at different frequency bands located between 402 MHz and 2483.5 MHz (e.g., MICS - Medical Implant Communication Service: 402-405 MHz). Very low bandwidth (0.3-1 MHz), 10-79 channels available, transfer rate between 75.9 and 971.4 kbps. Both NB receiver subcategories have specific disadvantages: ZigBee receivers have an unfavorable energy efficiency, the non-ZigBee receivers tend to unwanted oscillations and interference effects.
Ultra wideband (UWB)	Mostly used for on-body transmission. Frequency band between 3000-5000 MHz (three available channels) or 6000-10000 MHz (eight channels); much higher bandwidth (499.2 MHz) and higher maximum transfer rate (between 394.8 and 15600 kbps) compared to NB and HBC. Low radiated energy, simple implementation, no unwanted interference effects with other wireless technologies.
Human body communications (HBC)	IEEE 802.15.6 establishes 21 MHz as center frequency for human body communication. Relatively low bandwidth (5.25 MHz), only one channel available, transfer rate between 164.1 and 1312.5 kbps. Powerful television and radio stations may use the same frequencies so that interference avoidance represents a particular challenge.

Table A3. Relevant Differences Between Wi-Fi and WiMAX (in accordance with Song & Isaac, 2014; Beer, 2016)

	Wi-Fi	WiMAX
IEEE Standard	IEEE 802.11 a/b/g/n	IEEE 802.16 d/e
Maximal data rate	400 (-600) Mbps	70 Mbps
Maximal range	20 m indoors 100 m outdoors	50 km
Operating Frequency	2.4 GHz and 5 GHz	2 – 6 GHz
Channel Bandwidth	40 MHz	1.25 – 20 MHz
OSI embedment	MAC layer and physical layer (Convergence protocol based on FHSS and DSSSS)	MAC layer and physical layer (Convergence protocol based on QAM and QPSK)
Encryption	RC4 and ACS	3DES and AES

About the Authors

Ulf Gerhardt works as a senior physician specialized in internal medicine, psychiatry, and psychotherapy. He directs a 146 bed clinic in Lower Saxony, Germany. In 2014, he also earned a health economics degree from the University of Nuremberg and became a PhD student in Information Management and Information Systems (IMWI, Osnabrueck University).

Ruediger Breitschwerdt was appointed to a Chair at the Institute for eHealth and Management in Healthcare, Flensburg University of Applied Sciences/ Germany in 2014. His main research interests are both mobilization (mHealth) and process-orientation of healthcare services.

Oliver Thomas has, since 2009, held the Chair of Information Management and Information Systems at Osnabrueck University. His research focuses on Business Process Management & Analysis, Product-Service Systems Engineering, IT Governance, Risk & Compliance Management and Mobile and Wearable Information Systems.

JITTA is a Publication of the Association for Information Systems
ISSN: 1532-3416