MY MOBILE AND SMART HEALTHCARE ASSISTANT

State of the Art

Per Use Case

Change History

Version	Date	Description	Affected Sections
V0.1	24/4/2014	Starting version (template, summary…)	All
V0.2	22/5/2014	Update	Chapter 1 and 7
V0.3	9/6/2014	Update	Chapter 8
V0.4	16/6/2014	Update	Chapter 1, 2, 3.1 and 3.7
V0.5			
V0.6	20/6/2014	Update for hypertension case	Chapter 3.5
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1 Introduction

This report provides an overview of the current state of the art of mobile healthcare applications as well as its enabling technologies. The report consists out of two sections.

The first section focuses on the enabling technologies, including network technologies, sensor technologies and analysis models. The second part focuses on competitive products in the mobile application market, which will be analysed and described per use case.

2 Enabling technologies

This section contains an analysis and description of technologies that enable successful development and implementation of the MoSHCA app. The analysis differentiates network technologies, sensor technologies and analysis models.

2.1 Network technologies

2.1.1 Bluetooth

IEEE 802.15.1, better known as Bluetooth is a wireless networking protocol created by mobile phone maker Ericsson in 1994. Its development is actively managed by the Bluetooth Special Interest Group (BT SIG). Bluetooth forms a radio network using the unlicensed “Industrial, Scientific and Medical” frequency band at 2400 MHz This band is unlicensed since microwave ovens operate at 2450 MHz, therefore the range 2400-2500 MHz has been reserved. Bluetooth uses only the first 84 MHz of this range, dividing it into 79 channels of 1 MHz plus guard bands. Channels are dynamically selected, avoiding channels in which other nearby devices are operating.

Bluetooth uses a master-slave architecture, which in the case of MoSHCA usually means that the smartphone acts as the Bluetooth master and the sensor as a slave. Complex sensors may use the Bluetooth scatternet mechanism, in which a bridge device works as master in to connect a number of independent sensor devices, and yet appears as a single slave device with the combined sensor results towards the master smartphone device.

Bluetooth devices come in different power classes, with class 3 limiting the radio power to 1 mW. This gives good battery endurance[1], but limits the range to about 1 meter. This is typically sufficient to connect a body-worn sensor to a smartphone carried at hip level.

Bluetooth is not a standard wireless networking technology under the IEEE 802.11 family of networking standards, and it instead defines its own higher-level protocols. Each device must support at least the fundamental protocols: *Link Management Protocol* (LMP), *Logical Link Control and Adaptation Protocol* (L2CAP) and *Service Discovery Protocol* (SDP). These fundamental protocols are described by the core Bluetooth Specification. For healthcare applications, the Bluetooth Medical Devices workgroup created the *Multi-Channel Adaptation Protocol (MCAP)* and IEEE 11073 adds a *Personal Health Device* (PHD) protocol. These protocols are layered as shown in Figure 1:

[1] Modern batteries can provide approximately 200 mW·h/g. A one gram battery provides enough power for approximately one week of continuous radio operation.

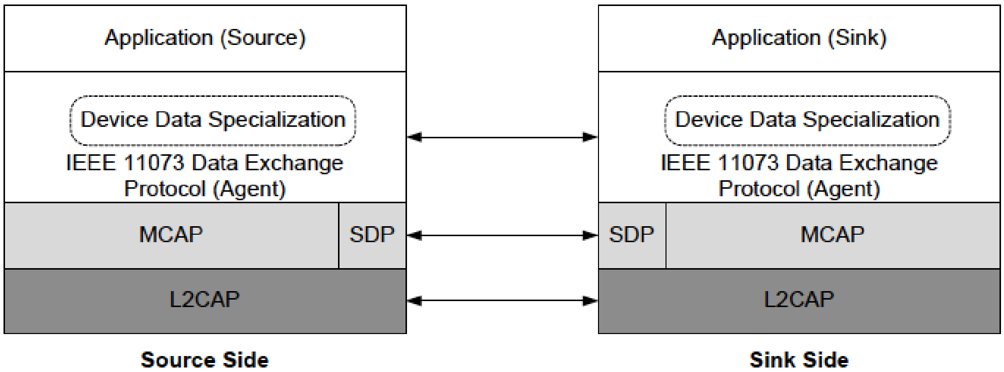


Figure 1. Protocols of the IEEE 802.11 standards.

For more information, please see Deliverable 2.2, specifically paragraph 6.1. A complete and current list of Bluetooth protocol standards is maintained on the Bluetooth developer website[i].

2.1.1.1 Bluetooth Low Energy

Of particular interest to MoSHCA is the Bluetooth Low Energy (BLE) extension, introduced in Bluetooth version 4.0. It is specifically designed for sensors in health care applications. The BLE system was created for the purpose of transmitting very small packets of data at a time, while consuming significantly less power. BLE is actively supported by the Continua Health Alliance[ii]. To differentiate the “classic” Bluetooth from the new Bluetooth Low Energy, the former is rebranded as “Basic Rate” (BR) Bluetooth

Devices that can support the Basic Rate Bluetooth and BLE are referred to as dual-mode devices and are branded Bluetooth Smart Ready. Devices that only support BLE are referred to as single-mode devices and are branded Bluetooth Smart.

Bluetooth low energy devices are optimised for low power consumption, which results in less high data rates, and relatively short connections. BLE can create a connection, send data, and gracefully disconnect in about three milliseconds. As a result, power consumption is reduced by one or two orders of magnitude.

One of the basic concepts behind BLE is that everything has a state. This state is exposed by using the Attribute Protocol in an Attribute Server. A state could be anything: the current temperature, the state of the battery of the device, etc. Some states can also be written, for example a thermostat temperature setting.

BLE uses both a client-server architecture and a service-oriented architecture. The main benefit of the client-server architecture is a defined split between the client and the server. This is necessary when different parts of the system are on different devices. By defining one of these parts as a server and one as a client, the explicit relationship between these two parts of the system can be determined.

The service-oriented architecture organises the information in a server into services. These services can be discovered, interacted with and used with known semantics. For a service to be considered a service, it must follow a formal description of both its exposed functionality and how it behaves. The Bluetooth Core Specification[i] is the primary list of such services. To discover and interact with these services, a program running on a Bluetooth host uses the Bluetooth Attribute Protocol, also documented in the Bluetooth Core Specification. In particular, service discoverability is described in the protocol profile, the Generic Access Profile.

The controller is typically a physical device that can transmit and receive radio signals and how these signals can be interpreted as packets with information within them. The host is typically a software stack that manages how two or more devices can communicate with one another and how several different services can be provided at the same time over radios. “Apps” in figure 2 include both the MoSHCA application and the BLE-connected sensors.

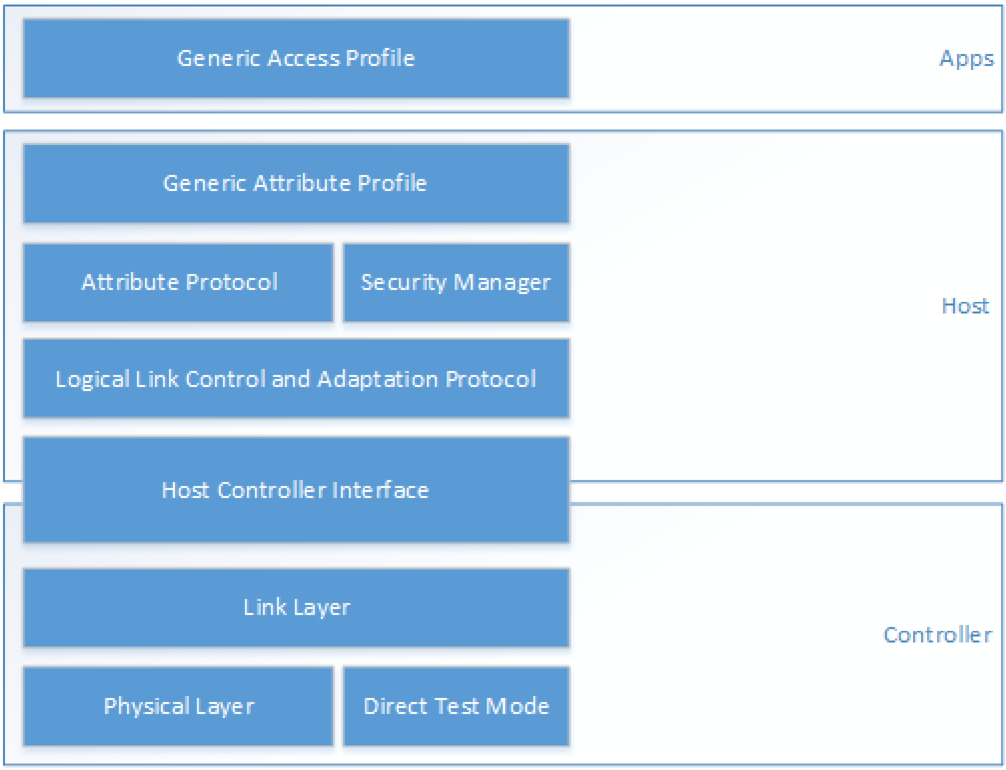


Figure 2: Bluetooth Low Energy Architecture

A main influence on energy consumption of the BLE protocol is the design of *connections*. Connections allow application data to be transmitted reliably and robustly. The data sent in a connection can be acknowledged, integrity is protected by CRC and to protect privacy the data can also be encrypted. Connections are always starts when a Bluetooth master device sends a connection request packet to the slave device, which can only happen in response to an advertisement packet.

2.1.2 WiFi

WiFi is a marketing name for a number of wireless network technologies in the IEEE 802.11 series of network standards. Initially specified at only 2 Mbit/second, the first popular version became the updated 802.11b variant which could transmit 11 Mbit/second. Like Bluetooth, the 802.11b standard uses the 2400

MHz ISM band. While the standard defines up to 14 bands in this range, only 3 of them can be used concurrently (by convention 1, 6 and 11).

Another early WiFi variant is 802.11a, which uses a slightly different modulation (OFDM instead of DSSS), but more importantly uses the ISM band at 5 GHz. Due to international disagreement about the exact position of that ISM band and manufacturing challenges, 802.11a was less popular even though the band offered higher throughput (typically 12 non-overlapping channels at 54 Mbit/second).

As WiFi became popular with consumers and businesses, updates 802.11g and 802.11n were adapted. 802.11g brought OFDM (as used by 802.11a) to the 2.4 GHz band (as used by 802.11b), and thereby could achieve the same 54 Mbit/second speed. With some squeezing of channel width, it became possible to use channels 1, 5, 9 and 13 concurrently. 802.11n added the ability to use multiple antenna's concurrently, by using Spatial Multiplexing. Under ideal conditions, it can reach 600 Mbit/second, but this assumes no contention from other sources.

2.1.3 Long range wireless networks 2G/3G/4G

While Bluetooth and WiFi are Wireless Local Area Network technologies, 2G/3G/4G refer to 3 generations of long-range wireless networks used in the telecom industry. These use licensed radio frequencies and a cellular network with radio base stations operated by a Mobile Network Operator (MNO).

The obvious "missing" generation would be 1G. This is the label applied to a number of analogue cellular telephone networks, such as AMPS in the USA and NMS in Northern Europe. Since these were specifically intended for telephone use, they were not designed to carry data. And being analogue, they were quickly replaced by digital cellular networks.

The dominant second generation network technology was GSM (*Global System for Mobile Communications*). The first digital cellular network included a data transport service early on, known as CSD (*Circuit Switched Data*). This allowed a 9.6 Kbit/second data stream, using the same 900 MHz frequency band that was also used for audio signals.

As GSM became popular, it was expanded into different frequency ranges (1800 MHz in Europe, 1900 MHz in the USA, 450 MHz) and enhanced data networking was realized with the introduction of GPRS (packet switching on GSM network) and EDGE (improved modulation and coding scheme).

Even with the EDGE extensions, GSM was limited by its basic design fundamentals, in particular its use of radio channels. The 3G generation of standards solved this problem. Most commonly encountered of the 3G standards is UMTS, because of its interoperability with GSM. However, it replaced TDMA with W-CDMA (*Wideband Code Division Multiple Access)* at 2100 MHz. This allowed higher bandwidths, currently reaching as high as 168 Mbit/second. Due to these benefits, many frequencies originally used for GSM are now being repurposed for UMTS.

With 4G, even higher data speeds can be achieved. Again, there are multiple standards within this generation, and there is a dominant standard: LTE (*Long term Evolution*). It too is interoperable with GSM and UMTS. Its main benefit is a higher speed, achieved by simplification of the core network. The downside is that the LTE standard is defined for many frequencies, but operators and devices do not always agree on supported frequencies.

2.2 Sensor technologies

This section will focus on the sensor technologies required in the MoSHCA use cases.

2.2.1 Micro-spirometer

A spirometer is a sensor that measures lung function and it is the most common pulmonary test. There are many different types of spirometers, but most of them involve the measurements of the volume and flow of breath during inhalation and exhalation. A flow sensor is typically used to measure the volume and direction of the breath flow. Inspiration is particularly important when assessing possible upper airway obstructions. For diseases such as COPD, the most common parameters in spirometry are related to the exhalation, in particular parameters such as the forced expiratory volume (FEV), the volume exhaled within the first second of a forced expiration (FEV1) and characteristics of the exhalation curve.

2.2.2 Pulse-oximeter

Pulse-oximeters are non-invasive sensors for measuring oxygen saturation using the principle of photometry. The way it works is that a small light source emits light through a body part (usually the finger, earlobe or the tongue). Some of the light is absorbed by the arterial blood, depending on the amount of oxygenated hemoglobin present in the blood. Changes in the wavelengths are measured, which is then used to determine the saturation of oxygen in the blood, expressed in percentages (100% is full saturation). These sensors are common in hospitals, portable versions are becoming available for eHealth applications.

2.2.3 Baby pulse-oximeter

Usually, a pulse oximeter can be used in adults and babies. Grown-ups would place the sensor on a fingertip or an earlobe, in the case of infants it is placed across a foot or a hand.

2.2.4 Glucometer

Glucometers are sensors that measure the level of glucose in blood. They are mostly used by patients diagnosed with diabetes mellitus or hypoglycemia. The concentration of glucose in blood is generally given in g/L or mg/dL or mmol/L. They are associated with disposable strips that usually contain an enzyme called glucose oxidase positioned on an electrode interface. They then react with the glucose molecules. When the strip is inserted into the meter, the flux of the glucose reaction generates an electrical signal that can be measured and that gives a direct indication on the level of glucose in blood. The blood sample is taken directly after pricking a patient’s fingertip.

2.2.5 Hemoglobin photometer

Hemoglobin is an oxygen transport protein in the red blood cells of humans. While pulse oximeters measure the amount of hemoglobin of that is oxygenated, hemoglobin photometers measure the amount of hemoglobin in the blood. For example, a deficiency in hemoglobin, called anemia, may indicate problems such as nutritional deficiencies, bone marrow problems or kidney failure. High hemoglobin may also indicate certain disorders, such as the preeclampsia syndrome. While, at the moment, hemoglobin testing is done at a laboratory, hemoglobin testing can now also be done at home using electronic equipment.

2.2.6 Blood pressure meter

For hypertension, a blood pressure device (Figure 3) is a key component to measure a patient’s blood pressure. In the market, we can have various vendors for blood pressure device at low prices. Most products use a non-invasive blood pressure determination using the "oscillometric methods". The blood pressure device refers to any measure of vibrations caused by the arterial pulse. A blood pressure device detects the pulsatile pressure generated by the arterial wall as it expands and contracts against the cuff with each heartbeat.

There are two types of method to measure blood pressure:

- Invasive
  - Pressure catheter and transducer
  - Accurate reproduction of central pressure waveforms
  - Risk of thrombosis and arrhythmias
- Non-invasive
  - Auscultation by era or automatically by sensor with cuff: need in skilled hands
  - Oscillometry + cuff: for the MoSHCA project. Less subjective and good for self-management at home with easy to use at low prices.
  - Volume clamp: Sensitivity is good but limited to peripheral arteries
  - Tonometry: sensitivity is very good but only used for superficial vessel
  - Quick, cheap, and widely used

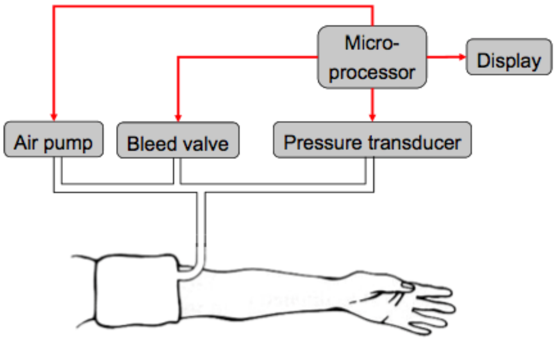


Figure 3: The basic diagram of blood pressure measurement based on the oscillometric with cuff

The principle of oscillometry used an algorithm that calculates a filtered signal of cuff pressure between systolic and diastolic waveforms. To detect the pulse signal among noisy input, this filter algorithm removes inputs which are a-periodic. This makes the value is unreliable in patients with irregular pulse like patients in shock.

The blood pressure measuring process for cuff device consist of the following steps:

- Sit comfortably with your arm resting on a flat surface so that the centre of upper arm
- Lay left or right arm on the table
- Put a cuff in the right position and fasten securely
- Press a measurement button in a blood press device

2.2.7 Heart rate sensor

- A heart rate monitor is a device to measure the heart rate (number of heart beats per minute). This device can help to detect heart malfunctions.
- The signal acquisition is the first consideration to implement a heart rate monitor. The electrodes in the

skin detect the small voltages in the order of hundreds of microvolts generated by the heart activity.

- The acquired signal is filtered and amplified by a signal conditional module and transferred to a target device or module by data bus or wireless technologies.

2.2.8 Breath rate sensor

Body sensor for extracting the respiration rate based on the amplitude changes in the body surface potential differences between two proximal body electrodes. The sensor could be designed as a plaster-like reusable unit that can be easily fixed onto the surface of the body. It could be equipped either with a sufficiently large memory for storing the measured data or with a low-power radio system that can transmit the measured data to a gateway for further processing. The estimated sampling frequency is 25 Hz and range between 0 and 120 BPM

2.2.9 Force sensor

2.2.9.1 Force sensor (in shoe)

For the mobility use case, the balance of a patient will be determined by measuring the loading patterns of this patient on his two legs, and specifically by considering the differences between those two loading patterns. By continuously measuring the forces that a patient exerts on each of legs these two loading patterns can be determined. In order for this use case to fully satisfy all objectives, the forces need to be measured and collected in real-time. For that reason a wireless force sensor has been developed that a user can place in a specially designed shoe. This sensor sends its 50Hz measurement data via Bluetooth 4.0 (BLE) to a data aggregator. By using two sensors, one for each leg, the two loading patterns can be collected. The data aggregator is a small device that the user can wear on his belt or, akin to a watch, around his arm. The aggregator forwards the two measurement signals to the smart phone by Bluetooth.

2.2.9.2 Force sensor (in bed-mat)

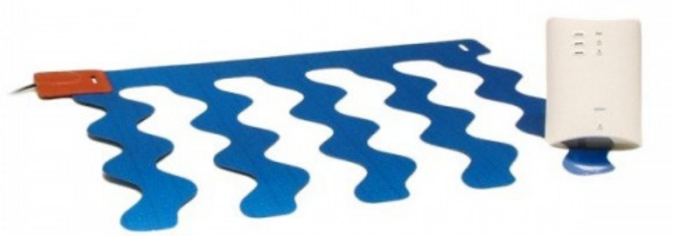


Figure 4: Bed-mat force sensor

A bed sensor (Figure 4) is a flat mat type device that is used in a bed. It is designed to detect movement when a person is experiencing tonic-clonic seizures during their sleep. Since accurate detection depends on type of bed, mattress, and the size and weight of the person the sensors needs adjustment to compensate for these variables. The sensor consists of a thin sheet metal that is positioned between two mattresses. When movements on the bed are faster than normal movements like turning, the monitor detects this as the clonic-phase of tonic-clonic seizure.

During a convulsive seizure, body movements are detected by the sensor from under the mattress. A microprocessor analyses the movements to determine if they are seizure typical and if an alarm should be raised. The notification triggers if the faster movements continue for longer than the pre-set delay. Typical delay times vary between 10 to 20 seconds. Response times can be very quick from 5 seconds to 20 seconds depending on the alarm delay setting.

Since seizures vary per individual it is virtually impossible to guarantee that all seizures from all patients will be detected, especially from younger, lighter patients. Generally for teenagers and adults a bed sensor will detect convulsive seizures.

2.2.9.3 Force Sensor (in baby scale)

A Scale is a measuring instrument for determining the weight or mass of an object. Weighing scales are used in many industrial and commercial applications, and products from feathers to loaded tractor-trailers are sold by weight. Specialized medical scales including infant medical scales, and bathroom scales are used to measure the body weight of human beings.

Electronic scales allow weighing with great accuracy; Scales come in all shapes, sizes and configurations, but the basic component doing the measuring is nearly always a load cell.

A load cell is a kind of transducer, a device that converts one form of energy into another. Through load cells, digital scales change mechanical energy into an electrical effect. The widely used strain, for example, reads compression or tension as tiny changes in electrical resistance in a Wheatstone bridge

As a load cell measures compressive resistance change, it transmits a signal to the CPU, which converts it into input for a display board, which then shows the result on a digital screen. This principle remains true whether you use a strain gauge or some other kind of measuring device.

Industries that require greater safety and sterility often turn to pneumatic load cells, which derive the weight of an object by measuring the air pressure necessary to balance it. These blowhards work well in the food industry or within hazardous sites because they don't contain fluids that might seep, drip or spurt into the environment. Pneumatic cells can heft a wide range of weights with high accuracy, but they require a clean, dry atmosphere and take a long time responding.

Hydraulic load cells, which measure load as a change in fluid pressure, are commonly found weighing tanks, bins and hoppers. Because they function with no electricity, hydraulic cells work well in locales where power is not available. These cells are usually expensive and complicated but rugged.

But a buyer looking for a scale might also consider a cell's size, shape, configuration, materials and other physical aspects based on the job requirements involved. Form factors are also chosen for their ability to minimize the effects of extraneous forces. Scales typically measure force along a single direction called the principal axis. Weighing errors arise mainly from off-axis forces, which act parallel to the load, and from side loads, which act perpendicular to it. Thanks to their zigzag design, s-beam load cells excel at eliminating side loads.

2.2.10 Camera

Cameras are standard equipment on smartphones and can be used as an alternative for various external biosensors. Some particularly interesting ones are for example:

- Analysis of chemical indicator strips: in the pregnancy use case (Section 5.7), we use the camera to analyse the colour of a chemical indicator strip for measuring protein and creatinine in the urine.
- The camera has also been used to replace other biosensors. For example, [Scully et al 2012][iii] developed an app that records a video clip while a patient's fingertip is pressed against the lens of the camera. By analysing the changes in light reflected by the blood in the finger, this allows the program to compute various physiological parameters such as blood oxygen saturation.

Earlier, cameras have been used as an external device or built-in in laptops, webcams, for communication over the internet. Nowadays, more and more doctors and practitioners are taking advantage of this common usage to reach patients from different cities, expanding the number of patients they can treat as well as the treatment. These cameras appeared in the early 90s at the same time that camera-on-chip - Complementary metal–oxide–semiconductor (CMOS) - was presented. CMOS cameras replaced in time the earlier charge-coupled device (CCD) technology for imaging

2.2.11 Photo detector

The photo detection is needed when tracking a patient location and presence in restricted area. For wake and sleep monitoring with accelerometer, photo sensor recognized the light by transmitter like an infrared or a photoelectric receiver.

2.2.12 Accelerometer / Activity monitor

An accelerometer measures acceleration. Modern MEMS (Micro Electro-Mechanical System) accelerometers usually do so by suspending a small proof mass from a microscopic cantilever. Under acceleration, the cantilever will bend. This displacement changes the capacitance of the sensor, which can be converted back into acceleration. Normal accelerometers can measure accelerations up to approximately 100 meters/second² with 10 bits resolution (i.e. 0.1 m/s²). More specialized accelerometers can measure far higher accelerations, such as would be observed in a high speed car crash.
A single cantilever can measure acceleration along one axis, but acceleration is a vector. More advanced accelerometers therefore are two-axis or three-axis designs. Gravity is an acceleration which is always present and fairly constant, so these multi-axis accelerometers can also be used to measure tilt.
MEMS accelerometers can be produced cheaply and are found in many modern electronic devices, such as smartphones and electronic scales. They are also commonly used in training devices for sports, as well as healthcare devices
For the MoSHCA project, an accelerometer will be used in an activity monitor. The activity monitor attached the multi-axis accelerometer to the body, and algorithms recognize the pattern of movement. Algorithms used for this purpose vary from simple to extensive, depending on the desired outcome. There is an active field of research that is currently developing and testing ever more advanced processing algorithms to calculate for example energy spent or to identify the type of activity in which the user of the accelerometer has engaged (walking, cycling, sleeping, etc.). An example of such a processing algorithm (relevant for MoSHCA) calculates the number of steps of a walking person. This leads to results such as displayed in Figure 5. In a more complex application, specific movements of an epileptic patient may be an early warning sign of an upcoming seizure.

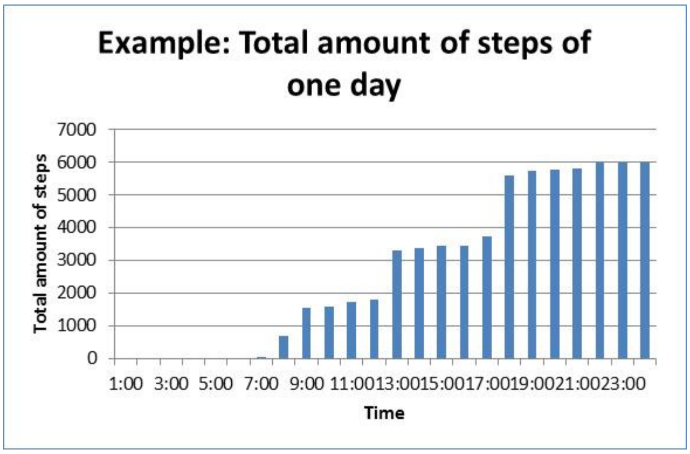


Figure 5: Monitoring of number of steps during a day.

2.2.13 Posture indication sensor

Posture sensor measures relative postures: vertical, horizontal or oblique postures of a person. An embedded accelerometer and its instant three-axis values are processed to detect a body position. The sensor is capable to calculate degrees offset from the 0º that corresponds to a vertical stand position and 180º to an inverted vertical position. -90 and 90º correspond to horizontal positions. Quick position changes, e.g. from 0º to 90º in a certain short time means a possible patient fall during a measuring session.

Different patterns are compared in order to detect different positions or events (falls, incorrect movements, etc.). Estimated Sampling Frequency is 1 Hz. Dynamic range between -180º and 180º

2.2.14 GPS

GPS technology included in all Smartphone models available in the market nowadays, offers the possibility to obtain a good precision in performance analysis through position and velocity of a motion body using satellite triangulation methods.
MoSHCA takes advantage of this technology in order to monitor data related to workout session of the patient:

- Distance/route taken in the workout session
- Instant and average speed of the session

A basic requirement to be able to get information from the Smartphone GPS is the location of the session, it must be outdoor or at least without severe physical obstacles above the person in order to get direct connectivity to the GPS satellites.

2.2.15 Microphone

Microphones are very familiar sensors; every phone has one. On modern smartphones, these microphones are not only used to make phone calls, but are also available for audio capture and processing. This enables their use for the MoSHCA project.

Smartphone microphones are necessarily small, and must be energy-efficient. This limits the choice of available microphone technologies. In addition, cost is an important factor in mass-market smartphones.

Therefore many smartphones use “electret” microphones. In an electret microphone, a small piece of electrically charged Ferro-electric material (the electret) is attached to a diaphragm. Sound waves cause the diaphragm to vibrate, and the electret to move. The moving dipole charge can directly drive a pre-amplifier.

The condenser microphone, an older design, has made a comeback in recent years. Like the electret, it detected sound by the movement of an electrical charge. But where the electret is a permanent dipole, a condenser needs to be permanently powered. However, modern MEMS technology (Micro Electro-Mechanical Systems) has allowed the miniaturization of the condenser element, which has also decreased the power usage. This makes the MEMS condenser microphone a possible alternative to electret microphones.

2.2.16 Multi-sensor devices

Several of the aforementioned sensors can be combined into a single device.

2.2.16.1 Body exercise band / wrist band

Wristbands can be worn 24/7, and measure such aspects of health as activity, vital signs such as heart rate, calorie management, sleep monitoring, and personalized data representation in the form of smartphone / cloud management. Such measurements are taken through the use of on-board acoustical, optical, temperature and acceleration sensors, and then relayed to a synced smartphone via Bluetooth.

Figure 6: Body exercise band

The body exercise band (Figure 5) is a physiological monitoring telemetry device intended for monitoring of adults in the home workplace and alternate care settings. The device consists of a chest strap and an electronics module that attaches to the strap. The device stores and transmits vital sign data including heart rate, Breathing Rate and Posture indication. Indicated for use as a general patient monitor to provide physiological information as part of an occupational welfare monitoring system, for general research and performance measurement purposes, or where prescribed by a healthcare professional.

2.2.16.2 Embedded Smartphone Sensors

MoSHCA can take advantage of the fact that modern smartphones already contain an array of sensors, such as cameras, microphones, GPS receivers, accelerometers, etcetera. For the MoSHCA use cases, the camera and microphone are especially interesting.

2.3 Analysis models

In this section, we provide an overview of the basic technologies which enable reasoning with contextual information that the consortium considers particularly useful for mobile health applications. The first category of models we consider are *rule-based models*. Such models could be learned from data (e.g. using decision trees) or derived from expert knowledge. The second kind of model we consider are *linear models,* which describe a linear relationship between variables, with support vector machines (SVMs) as an example. Then we describe *neural networks* as an example of a non-linear model. Then we move to *probabilistic models*, including logistic regression and Bayesian networks. Finally, we introduce two *distance-based models,* with nearest-neighbour and case-based reasoning as two examples. For each of these methods, we also provide a brief overview of related work on mobile platforms. When appropriate, we outline the contribution of MoSHCA compared to the existing work.

2.3.1 Rule-based Systems

In the early 1970s, Alan Newell and Herbert Simon introduced the notion of a *production system* as a psychological model of human behaviour [2]. In this model, part of the human knowledge is being represented in separate units called *productions* or *production rules*. These units contain information concerning actions a person has to take upon the perception of certain stimuli from the environment. Such actions may affect a person's view on the environmental reality, on the one hand because previous assumptions may have to be revised, and on the other hand because possibly new phenomena have to be explained. Usually, rule-based systems are based on production rules, although they may also be learned from data. For example, decision trees (see e.g. [1]) could be considered a model consisting of a number of rules that lead to a particular conclusion.

The formalism has for example been used in the Heuristic DENDRAL system for predicting the molecular structure of compounds [3]. Part of the knowledge necessary for the purpose of this system has been encoded by means of production rules. The greatest success of the formalism, however, came with the building of the MYCIN and EMYCIN systems [4], in which the suitability of production rules for building diagnostic intelligent systems was convincingly shown. Another successful system, more directly employing the work of Newell and Simon, is OPS5, and its successor CLIPS (*http://clipsrules.sourceforge.net*). A more recent system that employs production rules is DROOLS (*http://www.jboss.org/drools/*).

The general architecture of a rule-based inference engine involves two principal components: a series of rules and a database (the *fact set*) to which the rules are applied. The rules have two parts, an *if-clause* (describing the conditions) and a *then-clause* (describing the action to take). A condition is built from a *predicate* and two associated arguments: a variable and a constant. By means of its predicate, a condition expresses a comparison between the specified constant value and the actual value(s) the specified variable has adopted. In the context of production systems, a predicate is a function which upon evaluation returns either the truth value *true* or the value *false*. A conclusion is built from an *action* and two associated arguments. An action can be considered to operate on a variable. The most frequently applied action is *add*, which adds the constant specified as its second argument to the value set of the multi-valued variable mentioned in its first argument; in case of a single-valued variable, the action *add* assigns the constant value from its second argument to the specified variable. The following rule illustrates some of these concepts:

if
lessthan(*age*, 60) **and**
same(*diet,healthy*) **and**
notsame(*exercise, low*)
then
add(*risk,low*)
fi

If this action is the only one specified in the consequent of a production rule, then the rule closely resembles a logical implication, in which the conditions of the rule appear on the left of the implication symbol and the conclusions are specified on the right of it. This interpretation, however, is no longer valid when actions other than *add* have been specified in the consequent of a rule. Consider, for example, the action *remove* which upon execution cancels the assignment of a specific constant to a single-valued variable, or deletes a constant from the set of constants of a multi-valued variable. A production rule in which this action has been specified cannot possibly be viewed as a logical implication.

Two inference methods are *forward chaining* and *backward chaining*. In backward chaining, rules are evaluated based on a particular goal, e.g., a particular conclusion you would like to draw. More popular with rule-based systems is a forward chaining strategy where rules are applied based on the available data, i.e., it is data-driven. Efficient algorithms have been proposed to enable forward chaining, in particular the Rete algorithm [5].

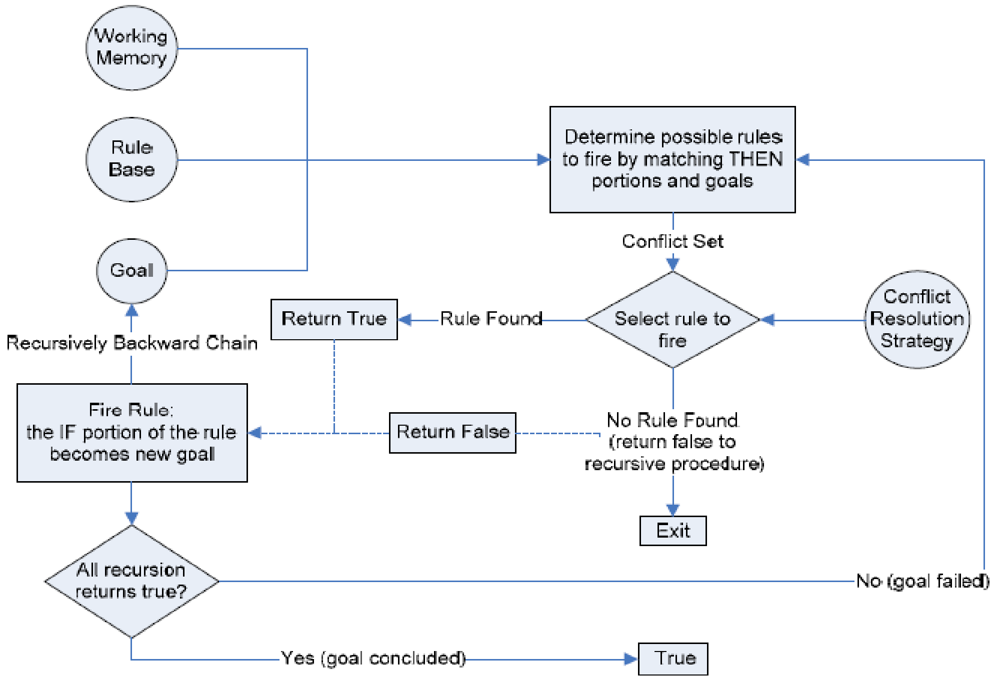


Figure 7: Architecture of a backward chaining system.

To illustrate backward chaining, consider these example rules:

1. **if** *Fritz hops* **then** *Fritz is green* **fi**
2. **if** *Fritz is green* **then** *Fritz is a frog* **fi**

Suppose that the goal is to conclude that Fritz is a frog given he hops. When using backward chaining, rule 2 is selected to be executed since its then portion matches the goal (Fritz is a frog). It is not yet known whether Fritz is green, and this way, the if portion of rule 2 becomes a new goal (Fritz is green). Rule 1 is now selected to be executed, since its then portion matches the new goal (Fritz is green). The if portion of rule 1 (Fritz hops) is known to be true as part of the first goal. This way, the initial goal can be concluded, i.e., that Fritz is a frog.

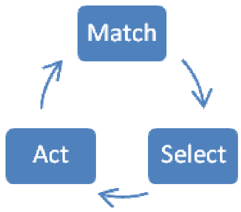


Figure 8: The Recognize-Act cycle in forward chaining.

In forward chaining, inference uses a Recognize-Act cycle, see Figure 8. In the matching phase, rules and data are matched in order to find candidate rules to apply, leading to a so-called conflict set. In the selection phase, one of these rules is selected based on a certain priority. Finally, in the act phase, the selected rule is applied, which typically changes the fact set. Using the new fact set, new matches are computed, etc. In the example above, given that we know Fritz hops, it is derived that Fritz is green, after which it is derived that Fritz is a frog.

Rule-based systems on mobile applications:
Rule-based systems have been used successfully for various medical applications, in fact, MYCIN that was used for the recommendation of antibiotics for bacterial infections, was one of the first applications of rule-based systems. Rule-based systems have also been applied successfully in mobile platforms, for example for cardiac patients monitoring [6, 7]. In this project, we will extend this work in several directions. One notable one is the adaptation of rules over time.

2.3.2 Linear Models

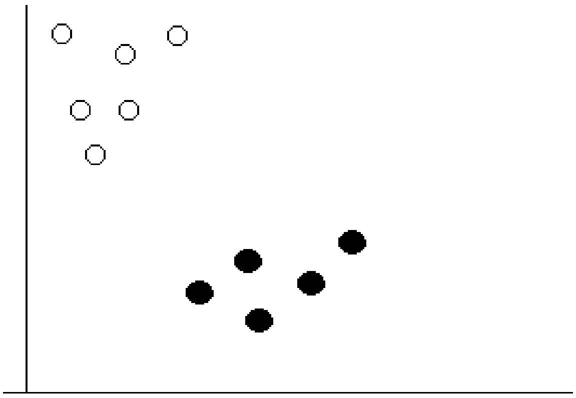


Figure 9: Labeled data.

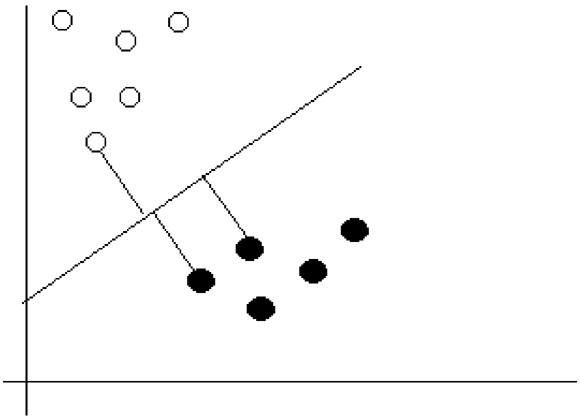


Figure 10: Distances of labeled points to a line.

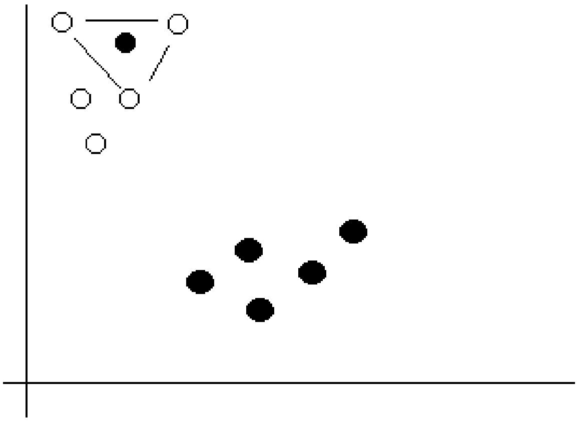


Figure 11: Example of data where linear models cannot separate data points completely.

Many times, a reasoning problem boils down to a yes or no question; either something matches or it does not. And often, this can be decided based on a small set of numbers. As an example, in the two-dimensional case on the left (Figure 9), points are either black or white. This is in fact a very easy case: there are many lines that would perfectly separate the black and white dots. But what would be the best separation?

The practical criterion is that we choose the line (or in general, the hyper plane) which offers the maximum separation between the two categories. In the figure on the left (Figure 10), this line is drawn at the same distance from the three closest points. Moving or tilting the line in any way would decrease the distance from the line to at least one point. Thus this line represents the best possible separation between the two sets of dots, and the three closest points in particular. These three points are therefore known as the support vectors, and the resulting classification of the two dimensional space in two parts is known as a Support Vector Machine.

Calculating this line is a straightforward process: it must somewhere between the closest pair, and cannot cross through either the cloud of black or white points. This means that we can ignore outliers: if there is no white point closer to black point X than to black point Y, then X is definitely not a support vector. Using the remaining possible vectors, it's a straightforward linear optimization process.

However, the same ease of calculation means that it is also generally impossible to calculate such a simple line dividing two such clouds of points. This is a real problem in practice when the colours/labels are assigned by human classification; humans will make mistakes. Having a single misclassified point in the middle of three other points makes it already impossible to find a solution. E.g. in the figure on the left (Figure 11), it is impossible to find a straight line separating black and white dots due to the mislabelled black point. Any line that separates that black point from one of its 3 neighbours will also put at least one white dots on the wrong side of the line.

To solve this, instead of rejecting a solution outright if it puts a point on the wrong side of the line, we assign it an arbitrary penalty value. That implies that if we choose a high penalty value, we will find a low margin of separation but few points misclassified; if we would choose a low penalty we will find a high margin and many points misclassified. If we have a reasonably assumption about the number of mistakes (but of course not exact knowledge), we can use this information in choosing the penalty. As long as the penalty is fixed, finding the equation of the separator remains a linear optimization process.

SVMs on mobile applications:
SVMs are popular methods for classification purposes. However, so far they are little work in applying these on mobile platforms. In the MoSHCA project, this technique is considered for the analysis of an audio signal. A similar application can be found in [8], where an SVM is used to use the smart phone for combining motion recognition with wireless positioning.

2.3.3 Neural Networks

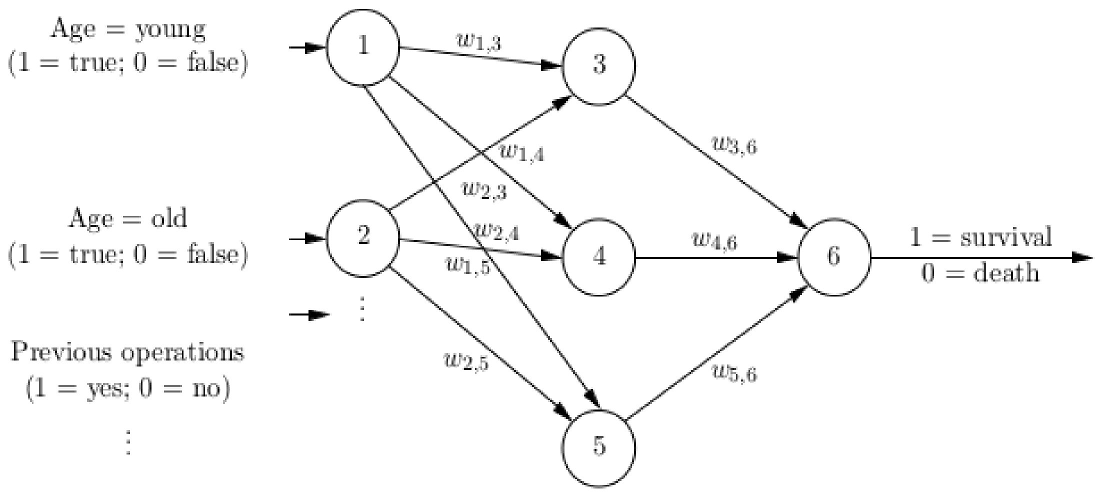


Figure 12: A 3-layer neural network [9].

A *neural network* (NN) [10] is a computational representation that takes as input a vector of (e.g. real) numbers, say encoded patient's features, and outputs a number (or a numerical vector) that is interpreted as, say, survival probability of that patient (see Figure 12).

The inputs are weighted and communicated to the nodes by edges. The nodes usually check if the sum of their weighted inputs is greater than a specific threshold and, based on the result, output 1 or 0 which are in turn weighted and conveyed to other nodes. Learning in NNs comprises of calculating the values of edge weights $w_{i,j}$ and node thresholds that can best explain the data. The learning algorithms are based on manipulating the weights and thresholds so as to minimise the error resulting from the discrepancy between the predicted value of the outcome according to the model and its expected value as indicated by a training set.

NNs are robust to noise in the training set and are capable of expressing complicated interactions, including nonlinear ones, among variables and hence are more flexible than regression analysis in statistics, where the particular type of function to be learnt (for example an exponential function $f(x) = a \cdot e^{b \cdot x}$) must be known beforehand. As with decision trees, one should beware of over-fitting. Although quite popular in AI research, NNs are not very suitable when human understanding of the relationship captured by the NN is important. This 'black-box' feature makes NN less attractive in for reasoning in medicine, where clinical credibility is essential. However, there are techniques that translate NN representations into symbolic ones.

Neural networks on mobile applications:
While neural networks are quite popular for classification, there are not a lot of mobile applications. One example is the use of neural networks for activity recognition based on data gathered from several accelerometers [11], though a decision tree outperformed neural networks in this study. As far as we are aware there are no convincing mHealth applications for this technique at this moment.

2.3.4 Logistic Regression

Logistic Regression is a type of probabilistic model that can be used when the variable of interest is a categorical variable with two categories, for example live/die, has disease/doesn't have disease, purchases product/doesn't purchase, wins race/doesn't win, etc. Despite its simplicity, logistic regression equations are still the models most popular for clinical decision support [12]. Note that, in contrast to the other methods described in this section, logistic regression is not considered an AI technique, but rather a standard statistical method. Nonetheless, it can be used as a basic method for building more complex models.

Logistic Model Formula

The idea of logistic regression is to transform a linear function to a $[0,1]$ domain. To explain this, we begin with an explanation of the logistic function, which always takes on values between zero and one:

$$f(z) = \frac{e^z}{e^z + 1} = \frac{1}{1 + e^{-z}}$$

and viewing z as a linear function of *an explanatory variable x (or of a* linear combination of explanatory variables), i.e.,

$$z = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n$$

which for example has been derived using an SVM (or least-square). The regression coefficients $\beta_0, \beta_1, \ldots, \beta_n$ represent the amount and type of influence the explanatory variables $x_0, x_1, \ldots, x_n$ have on the outcome. Negative values indicate that a variable decreases the probability of the outcome and a positive value of the coefficient means that an explanatory factor strongly increases the probability of the outcome.

The logistic function can be written as:

$$\pi(x) = \frac{e^{\beta_0 + \beta_1 x_1}}{e^{\beta_0 + \beta_1 x_1} + 1} = \frac{1}{1 + e^{-\beta_0 + \beta_1 x_1}}$$

This will be interpreted as the probability of the dependent variable equalling a "success" or "case" rather than a failure or non-case. We also define the inverse of the logistic function, the logit:

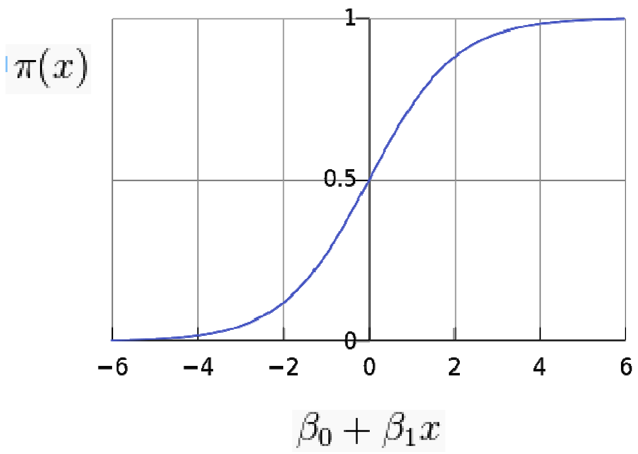
$$\frac{g(x) = \ln(\pi(x))}{1 - \pi(x)} = \beta_0 + \beta_1 x_1$$

and equivalently:

$$\frac{\pi(x)}{1-\pi(x)} = e^{\beta_0 + \beta_1 x_1}$$

A graph of the logistic function $\pi(x)$ is shown in Figure 8.

Figure 1: The logistic function.



The input is the value of $\beta_0 + \beta_1 x_1$ and the output is (x) . The logistic function is useful because it can take an input with any value from negative infinity to positive infinity, whereas the output $\pi(x)$ is confined to values between 0 and 1 and hence is interpretable as a probability. In the above equations, $g(x)$ refers to the logit function of some given linear combination x of the predictors, '$\ln\square$' denotes the natural logarithm, $\pi(x)$ is the probability that the dependent variable equals a case, β_0 is the intercept from the linear regression equation (the value of the criterion when the predictor is equal to zero), $\beta_1 x_1$ is the regression coefficient multiplied by some value of the predictor, and base *e* denotes the exponential function.

The formula for $\pi(x)$ illustrates that the probability of the dependent variable equalling a case is equal to the value of the logistic function of the linear regression expression. This is important in that it shows that the value of the linear regression expression can vary from negative to positive infinity and yet, after transformation, the resulting expression for the probability $\pi(x)$ ranges between 0 and 1. The equation for $g(x)$ illustrates that the logit (i.e., log-odds or natural logarithm of the odds) is equivalent to the linear regression expression. Likewise, the next equation illustrates that the odds of the dependent variable equalling a case is equivalent to the exponential function of the linear regression expression. This illustrates how the logit serves as a link function between the probability and the linear regression expression. Given that the logit ranges between minus infinity and infinity, it provides an adequate criterion upon which to conduct linear regression and the logit is easily converted back into the odds.

Practical Example

As an example of logistic regression, consider a study whose goal is to model the response to a drug as a function of the dose of the drug administered. The target (dependent) variable, Response, has a value 1 if the patient is successfully treated by the drug and 0 if the treatment is not successful. Thus, the general form of the model is:

$$Response = f(dose)$$

The input data for Response will have the value 1 if the drug is effective and 0 if the drug is not effective. The value of Response predicted by the model represents the probability of achieving an effective outcome: $P(Response = 1 \| Dose)$. As with all probability values, it is in the range 0.0 to 1.0.

One common question is "Why not simply use linear regression?" In fact, many studies have done just that, but there are two significant problems:

- There are no limits on the values predicted by a linear regression, so the predicted response might be less than 0 or greater than 1; clearly this is nonsensical as a response probability.
- The response usually is not a linear function of the dosage. If a minute amount of the drug is administered, no patients will respond. Doubling the dose to a larger but still minute amount will not yield any positive response.

But as the dosage is increases a threshold will be reached where the drug begins to become effective. Incremental increases in the dosage above the threshold usually will elicit an increasingly positive effect. However, eventually a saturation level is reached, and beyond that point increasing the dosage does not increase the response.

The logistic regression dose-response curve has an 'S' (sigmoid) shape such as shown in Figure 13.

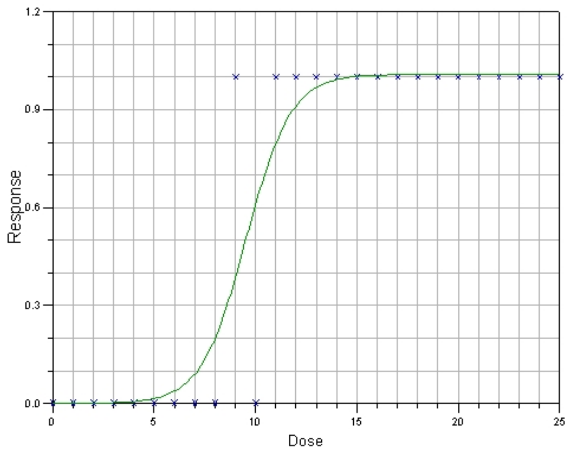


Figure 13: A logistic regression model.

Logistic regression on mobile applications:

Logistic regression models are abundant in medicine (see e.g. [13] for an overview), though it is often not reported as a technique for building mHealth applications. Instead, it is often used as a technique for building probabilistic models, which are then used for decision support. More details and examples where such models are used are provided in the next subsection.

2.3.5 Probabilistic Models and Bayesian Networks

For applications where uncertainty plays an important role, probabilistic models are often employed. Probabilistic models form a popular class of models in which uncertainty can be explicitly represented. In statistics, they are typically derived from logistic regression equations (as seen above), and can be manipulated using *Bayes' rule*. For example, we might know

$P\,(cure = yes \mid therapy = surgical\,)$

but if we would like to know the probability $P\,(therapy = surgical \mid cure = yes)$ (which percentage of patients who have been cured, have had surgery), the probabilities $P\,(cure = yes)$ and $P\,(therapy = surgical\,)$ would be required, because, according to Bayes' rule,

$P(therapy = surgical \mid cure = yes) = (P(cure = yes \mid therapy = surgical)P(therapy = surgical))/(P(cure =$

Both Bayes' rule and logistic regression equations allow the interpretation of new information in light of current knowledge, but do not provide a structured method for computing arbitrary probabilities.

In order to model a full probability distribution, Bayesian networks are a popular choice. A *Bayesian network* [14, 15], is a probabilistic graphical model represented as a pair $BN = (G; P)$. Here, $G = (V; A)$ is a directed acyclic graph consisting of vertices V , corresponding one-to-one to random variables of interest, and A are arcs, representing dependencies between variables. Furthermore, P is a joint probability distribution defined by a family of conditional probability distributions of the form $P(V_j \mid pa(V_j))$, that is, the probability that V_j takes on a specific value given the values of its parent variables, $pa(V_j)$. The network represents the joint distribution over the random variables, which can be factored according to the dependences represented in the graph, resulting in:

$$P(V_1, V_2, \dots, V_n) = \prod_{i=1}^{n} P(V_i \mid \mathbf{pa}(V_i)),$$

where $V_i \in V$ is the representation of a random variable in the graph G . Any probability of interest can be computed from this joint probability distribution.

A *dynamic Bayesian network* [16, 17], DBN for short, is an extension of a Bayesian network to a distribution over a sequence of random variables. It is particularly well suited to represents a Markov process

$X_1 \rightarrow X_2 \rightarrow \cdots \rightarrow X_t \rightarrow \cdots$

where X_t represents a random variable at a particular moment in time t . The joint distribution can be decomposed using the chain rule, writing $X_{1:T}$ for $X_1, \dots, X_T$:

$$P(X_{1:T}) = P(X_T \mid X_{1:T-1})P(X_{1:T-1}).$$

In general a DBN is a factorisation of a probability distribution, like its a-temporal counterpart. In addition, each X_t can be represent a Cartesian product of states, which in turn can be represented as a BN. This BN is called a *time slice* and relations between time slices can be modelled by introducing arcs in the graph between random variables in different time slices. A DBN factorisation can then be written as:

$$P(X_{1:T}) = \prod_t \prod_i P(X_{t,i} \mid \mathrm{pa}(X_{t,i}))$$

where i indexes variables within a time slice and $pa(X)$ denotes the parents of X in the graph. A hidden Markov model, a popular stochastic model used for pattern recognition, is a special case of a DBN.

A common assumption is that there is only a limited time frame that influences the current state of the process, as opposed to the complete history, which simplifies model learning. When assuming an nth-order Markov process we obtain:

$$P(X_{1:T}) = P(X_T \mid X_{T-1:T-n})P(X_{T-1:T-n}),$$

recursively. In the context of clinical data analysis, this assumption makes sense for two reasons: first, as time passes physiological and disease processes will change and older information will be less informative about the current state of the patient; second, it will often not be possible to obtain reliable information about the past. For smaller n more temporal independence is introduced and when only sparse data is available, it is common to make the most restrictive version of the Markov assumption, first-order, such that the future state of the process only depends on the present:

$$P(X_{t+1} \mid X_{1:t}) = P(X_{t+1} \mid X_t).$$

Hence, all parents of a variable X will be in the same time slice or in the previous time slice. From a medical point of view this means that the current health status provides the most information about the future. Given that clinical data is often sparse, an important practical consequence of this assumption is that it simplifies the model, and hence reduces the amount of data we need. When we now also assume that the process is *stationary*, that is $P(X_{t,i} \mid pa(X_{t,i})) = P(X_{t',i} \mid pa(X_{t',i}))$ for all t, t', we obtain a *two-slice* DBN consisting of an initial network BN_0 and a transition network $BN_{\rightarrow}$. A process through time can now be modelled by a sequence of 2 repetitions of transition networks. When modelling a chronic disease over a long period, it maybe that stationarity is not a reasonable assumption. For COPD one might argue that it is also useful to consider separate models for the disease stages (GOLD I-IV, Global Initiative for Obstructive Lung Disease; http://www.goldcopd.com). For example, it appears useful to consider recent techniques to learn non-stationary DBNs [18].

Bayesian networks on mobile applications:

There have been few approaches for using Bayesian networks in mobile devices. One of the reasons is that, until recently, mobile devices had insufficient resources for computing probabilities from Bayesian networks. There have been a few exceptions to this rule.

One area where Bayesian networks have been applied are context-aware recommender systems [19]. In this paper, they use the simplest kind of Bayesian network available, so called naive Bayesian network classifiers. In a naive Bayesian network classifier, the assumption is that the features that predict the class variable (in this case the context) are independent of other features, given the context. While this often leads to good classification performance, the models are not interpretable for domain expert, which is particularly important in areas such as medicine. Another example is restaurant recommendation on mobile devices using Bayesian networks [20].

A second area where Bayesian networks have been applied on mobile devices is in for the in and outdoor geo-positioning. For example, in [21], a simple dynamic Bayesian network is used to reduce noise from location sensors.

2.3.6 Nearest Neighbour

Nearest Neighbour Matching is a non-parametric method of pattern recognition. Like Neural Networks, the input signal consists of a vector of real numbers. The training set is similarly represented by a set of such vectors. With each of these vectors a possible outcome of the matching process is associated. This may be a label, a numerical value, or any other piece of data.

We can now define a distance or norm between vectors. Common choices are the L^1 (Manhattan) and L^2 (Euclidean) distances. We can then order the vectors in the training set by their distance to the given input. In the straightforward Nearest Neighbour Matching process, the result is simply the closest vector from the training set, its associated data, and the resulting smallest distance.

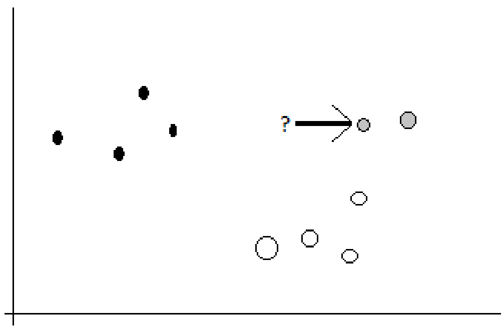


Figure 2: Example clustering data.

As an example, in the figure to the left (Figure 14) we have a two-dimensional space in which the training set vectors are labelled black, white and grey. The unknown input vector marked with “?” lies closest to the leftmost of the two grey vectors, and therefore will be classified as “grey”.

In reality, both the number of dimensions and the number of training vectors will be a lot higher. But as the search volume grows exponentially with the dimensionality, the number of vectors in the training set usually grows much faster than its dimensionality

In more refined nearest-neighbour models, the nearest *k* vectors are selected, and their associated data are combined. The method to combine this associated data depends on the nature of the data. E.g. when *k*=3 and the data consists of a simple label, the result of the Nearest Neighbour Match would be determined by a majority vote amongst the three labels of the closest vectors; in case of a three-way split the result would revert to the *k*=1 case. However, if the associated data is not a label but a number, *k* can take on any value, and the resulting *k* numbers can be weighted by distance.

The nearest neighbour model does not make any presumptions about the nature of each dimension. For instance, in sound analysis it is possible to take a Fourier Transform of the sound wave, and use the energy in each band as a dimension. However, as the input sound would become louder, its vector would be amplified equally in each dimension. Therefore it is generally mush more useful to take the normalized values, so that the vector length is always 1. E.g. using 9 bands and an L^2 distance norm, the vector associated with white noise would become $\left\{\frac{1}{3},\frac{1}{3},\frac{1}{3},\frac{1}{3},\frac{1}{3},\frac{1}{3},\frac{1}{3},\frac{1}{3},\frac{1}{3}\right\}$ regardless of the loudness.

Nearest neighbour on mobile applications:
As a general clustering method, nearest neighbour is very suitable for discovering clusters that correspond to some meaningful event, for example an activity in data extracted from accelerometers [22]. In the MoSHCA project, similar ideas will be applied to recognize certain events based on audio signals (see the use case for epileptic seizure detection in Section 4).

2.3.7 Case-based Reasoning

Case-Based Reasoning (CBR) is a methodology for developing knowledge-based systems that attempts to solve a given problem within a specific domain by adapting established solutions to similar problems [23, 24].

CBR has been formalized for purposes of reasoning and learning based on the exploitation of existing similar historical records as humans do. It has been argued that CBR is not only a powerful method for computer reasoning, but also a pervasive behaviour in every day human problem-solving; or, more radically, that all reasoning is based on past cases personally experienced. These features make CBR a good contender for any decision support system [25].

As can be seen in Figure 15, four main phases of action are defined in the CBR methodology: retrieve, reuse, revise and retain. It basically consists in retaining experiences as cases for a further reuse. Cases are registers containing a description of a problem and its solution. The aim is to reuse these cases for solving new problems by analogy. In presence of a new problem, the basic procedure consists of retrieving similar cases and reusing their solutions. Reuse implies an adaptation procedure of the retrieved solutions that is finished with a revision. After validation, the cycle is completed by retaining the solved situation (problem + new solution). These operations are known as the 4R of the CBR cycle.

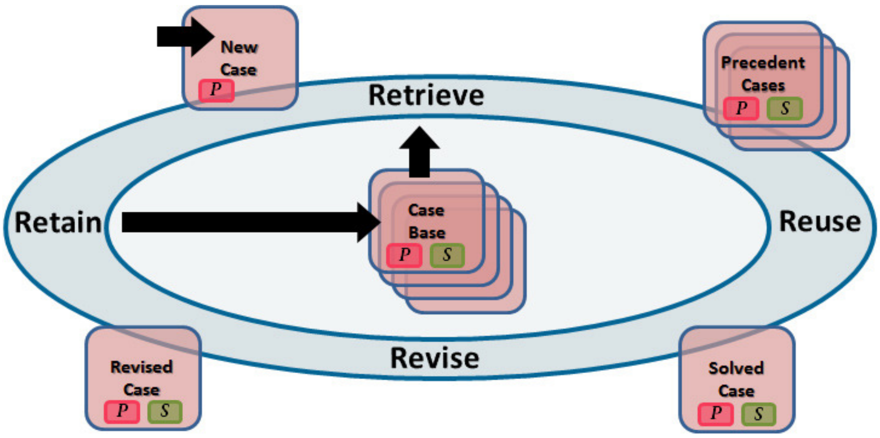


Figure 15: Four-step process (4R) of Case-Based Reasoning (based on [24])

CBR has already been applied in a number of different applications in medicine [26, 27]. CBR is appropriate in medicine for some important reasons; cognitive adequateness, explicit experience, duality of objective and subjective knowledge, automatic acquisition of subjective knowledge, and system integration [28].

On the other hand, contextual knowledge seems to be particularly relevant in medical applications, where inter-patients variability is extremely high, and where diagnostic and therapeutic decisions always need to be properly tailored to the single patient's peculiar situation. In [29], the author identifies three main directions in which contextual knowledge can be profitably resorted to within a CBR framework, namely:

- to reduce the retrieval search space, making the retrieval step faster and meaningful.
- the context-rich knowledge embedded in cases can help to maintain the overall knowledge content always valid and up to date.
- contextual information may be very helpful to adapt medical knowledge and reasoning strategies to specific local/personal constraints before applying them in practice.

CBR on mobile applications:
Currently there are some cases of applications for mobile using CBR. A field in which it is widely used is tourism [30, 31, 32]. In this field, CBR mechanism takes advantage of context information provided by the mobile to improve recommendations about the touristic sights that tourists might like to visit, taking into account the interests of other tourists. Variables such as country of origin or their general interests are

taken into account.

CBR on mobile applications has also been used in the field of smoking cessation (Ghorai, et al., 2013). The authors propose a system that displays motivational messages, or messages appealing to the ties that bind the users with their friends or family. These messages are personalized using CBR, which looks for similar cases among users being based on demographic variables, sex and age. The authors state that mobile-based messaging systems have already experienced acceptability when backed by the motivation to undertake certain behaviour changes, according to the results of several experiments. CBR enables in this case, the personalization of messages.

Another field of use is the recommendation of recipes [33]. They developed an application that asks the user what are the ingredients he has, and what are the restrictions when cooking regarding intolerance or dietary issues, and finally recommends recipes to cook. The authors' motivation of developing this application for mobiles instead of other running environments is the availability of consulting the recommender system while being in the kitchen.

Another example is a system of help to cell phone users [34]. It answers most frequent user questions related to operational problems and proposes answers, being based on previous cases with similar questions.

In conclusion, mobile phone applications using CBR are a growing interest line due to the collaboration possibility of the technique and the device. CBR provides context-sensitiveness and use of similar real cases, while mobile phones provide profiling and geo-location information, and the advantage of making recommendations in the place where users need it. Nevertheless, most of the CBR applications on mobile phones rely on running CBR in a back end, constraining the role of the mobile phone as the terminal to which interact with the system. The MoSHCA platform goes a step forward by placing the CBR system at the phone, so decisions could also be made in disconnection with the back end.

3 Similar products per use case

In this section, the objective, benefits, and principles of each use case are used to find similar products in the market. Using this method, a state-of-the-art market overview is gained in terms of competitive technologies.

3.1 General Health use case

3.1.1 Description of issue and how this is handled

Having good health and fitness is something almost everyone cares about. In those cases where a change in the lifestyle is required, either for an aesthetic or medical issue, the lack of knowledge about how to combine diet and exercise, and also in some cases the relation with some kind of medication is not an easy task. The medical knowledge is also an additional factor to be taken into account so as to adapt the guidelines of having general health to the specific conditions of each patient.

3.1.2 The MoSHCA solution for General Health

Objective:

The objective of this application is the promotion and accomplishment of a healthy life style based on the diet and exercise monitoring and the generation of recommendations. This solution will get more precise information coming from the exercise through sensors and analyzing the interrelation with medication and medical knowledge. Besides, the analysis of diet data will be adjusted to the user's medical profile considering several variables regarding the food and beverage intake.

Benefit:

The main benefit of this solution is the promotion, stimulation and performance of a healthy lifestyle based on diet and exercise, under the analysis and generation of recommendations founded on medical knowledge and data, avoiding general guidelines and non-needed visits to the doctor so as to follow the diet.

Innovation:

The principal innovations of this use case are:

- Integration of diet information with exercise information coming from sensors, besides the analysis of the possible interrelations with medications or health data, such as the presence of diabetes or cardiovascular diseases.
- Data crossing with medical knowledge and medication associated to each user.
- Customization of the ruled-based system considering medical data from the user so as to adapt the recommendation engine.

3.1.3 Similar products for the General Health use case

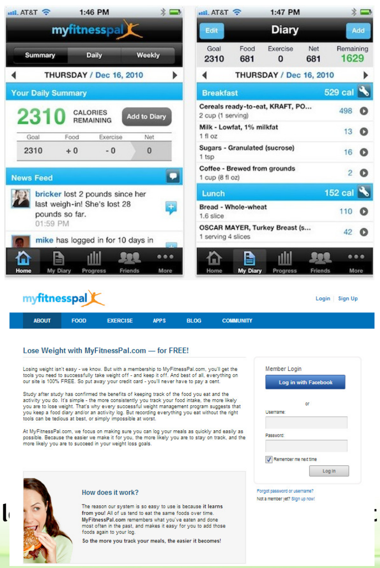
There are some similar solutions in the market regarding the diet monitoring, that in some cases are able also to introduce exercise data. Some of these applications are shown below:

1. **MyFitnessPAL** (http://www.myfitnesspal.com/)

This app boasts the largest food database of any iPhone calorie counter, with over 1.5 million foods available offline. With exercise tracking, sharing capabilities, goal setting and reports.

Advantages

- Multiplatform app (iOS, Android OS, Windows Phone, BlackBerry)
- Automatic synchronizing between App and web.
- Biggest food database
- Wireless data transmission
- Free app
- Connection with friends
- Customized goals based on your diet profile.
- Barcode scanner
- Save and reuse entire meals



- Recipe calculator - Enter your own recipes and calculate their nutritional contents
- Charts of progress over time
- Automatically post your progress to Twitter and Facebook

Disadvantages

- No sensors used to monitoring exercise
- No data crossing with health professional diagnosis

2. **MyNetDiary** (http://www.mynetdiary.com/)

MyNetDiary allows users to track food portions across a variety of serving sizes — including grams, ounces and cups — this removing the guesswork from data entry. Use your height, weight, age, gender and activity level to determine your daily intake.

Advantages

- Multiplatform app (iOS, Android OS, Windows Phone, BlackBerry)
- Automatic synchronizing between App and web.
- Big food database
- Free basic app
- Barcode scanner
- Save and reuse entire meals
- Optional blood glucose and diabetes tracking
- Medication tracking
- E-mail reports from the app, to print or share with your healthcare provider
- PhotoFoods service - if a food is not in the database or out-of-date, you can send its photos to add or update the food
- Customizing target macronutrient ratios
- Recipe calculator - Enter your own recipes and calculate their nutritional contents
- Charts of progress over time
- Voice dictation of foods
- Custom trackers - track anything you want, your mood, your sleep

Disadvantages

- No sensors used to monitoring exercise
- No data crossing with health professional diagnosis
- Limited basic mode, and expensive premium mode
- Mainly focused on diet and not on exercise tracking

3. **MyDietDiary** (http://www.medhelp.org/land/calorie-counter-app)

This application is a calorie counter app that tracks user's food, exercise, weight, water consumption… It records the food the user eats and calculates the calories consumed. Besides, it records the user's workouts and calculates the calories he burned.

Advantages

- Free application
- Easy graphics to interact with
- It is possible to access to the information stored from a PC
- It tracks food, exercise, water and weight

Disadvantages

- It is only available for iOS
- It does not consider medical knowledge
- No sensors used to monitoring exercise

4. **LoseIt !** (http://www.loseit.com/)

It is a diet app that features a free barcode scanner, a recipe builder, and a comprehensive database of food and activities. Users can add food to the database and track nutrients like protein, carbohydrates, and fat with this diet app.

Advantages

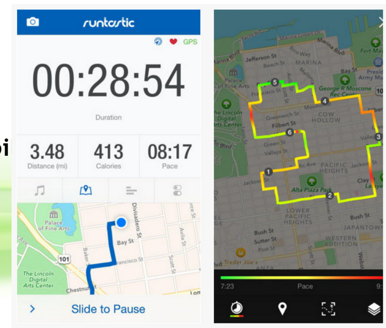
- It provides a bar scan functionality making easier finding and logging food
- It is available on Android, iOS, Nook, Kindle, and the Web
- It allows the sharing of food and recipes with friends

Disadvantages

- It does not track exercise information
- No data crossing with health professional diagnosis
- Limited basic mode, and expensive premium mode

Regarding the exercise monitoring, it can be also found many applications for smartphone. Some of them are shown below:

5. **Runtastic** (https://www.runtastic.com/)



The app tracks all kinds of metrics such as distance, time, speed and calorie consumption. It lets the user analyse every step he take, compare his routes, progress and speed and of course how many miles he clocks a week. It also has an integrated music player, heart rate monitoring and weather information.

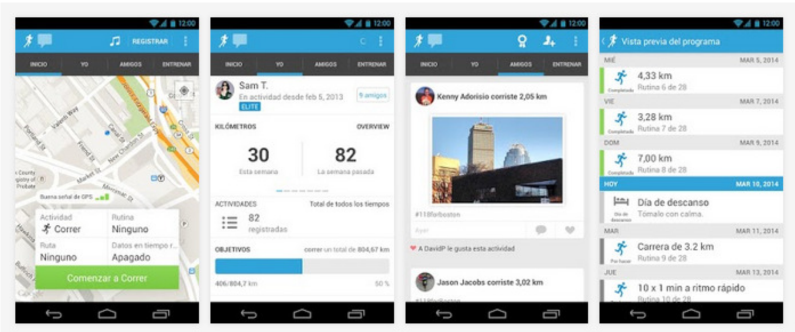
Advantages

- Multiplatform app (iOS, Android OS, Windows Phone, BlackBerry)
- It has statistics functionalities that can be shared with other users
- It has an integrated music player
- It presents detailed maps and personal diary to follow the training

Disadvantages

- It is only focused on exercise monitoring
- No data crossing with health professional diagnosis
- The exercise monitoring information only comes from the GPS and no other sensor is used

6. **Runkeeper** (http://runkeeper.com/)



It is an app that allows the user track his run, walks or bike rides. It shows the progress over the time and it is also connected with user's friends so as to track user's achievements and goals.

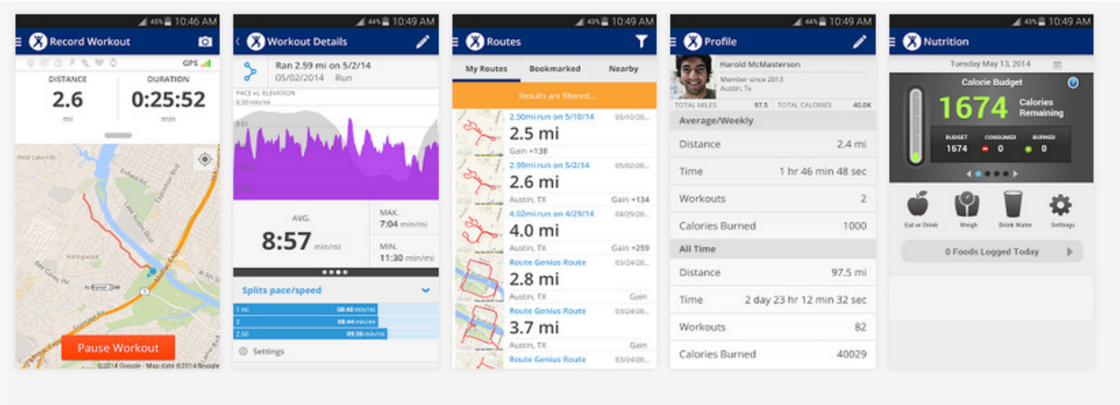
Advantages

- It is available for iOS and Android
- It has statistics functionalities
- It provides a notification functionality so as to encourage the user once his goals are reached
- It has media connections with Facebook and Twitter

Disadvantages

- The exercise monitoring information only comes from the GPS and no other sensor is used
- No data crossing with health professional diagnosis
- No diet information associated

7. **MapMyFitness** (http://www.mapmyfitness.com/)



The app allows users to explore and manage more than 600 fitness activities, meaning virtually anyone can tailor the app to their personal routines. It has a long variety of exercises and it allows following pre-defined routes or creating user's own ones.

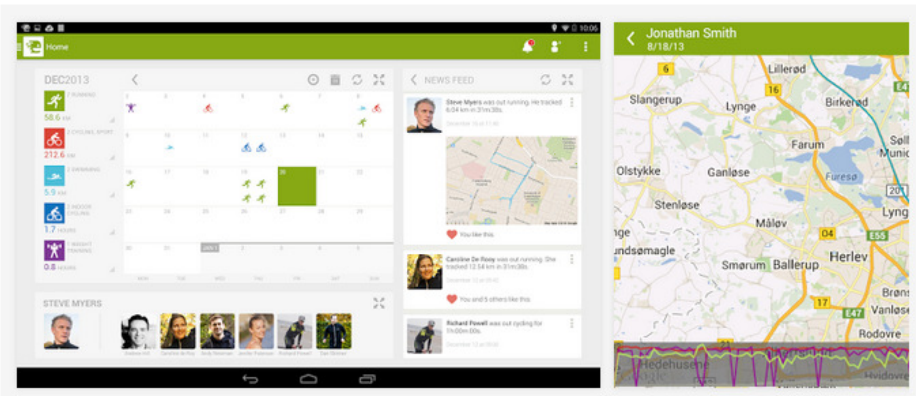
Advantages

- It is available for iOS, Android and Blackberry
- It allows sharing fitness activities with other people through email, Facebook and Twitter
- It creates and plans routes

Disadvantages

- The exercise monitoring information only comes from the GPS and no other sensor is used
- No data crossing with health professional diagnosis
- No diet information associated

8. **Endomondo** (http://www.endomondo.com/)



The app is a GPS-system which tracks how far users walk, run, bike, or travel during physical activity. Endomondo uses all that fancy tracking info to help connect on social platforms like Facebook, inspiring friendly competition or a digital boost of encouragement.

Advantages

- It is available for iOS, Android, Windows Mobile and Blackberry

- It provides a text-to-speech functionality based on the encourage of the users through messages sent by his relatives and friends
- It shows the route perform in the smartphone
- It is connected with Facebook
- It allows the customization of particular playlists for each practice

Disadvantages

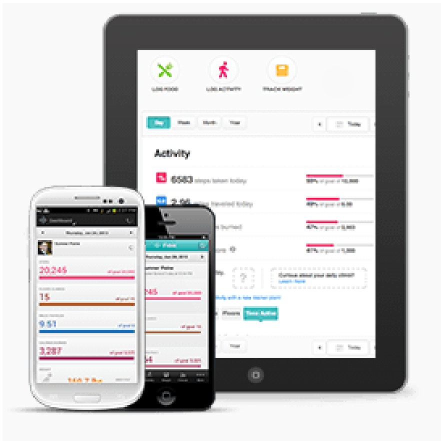
- The exercise monitoring information only comes from the GPS and no other sensor is used
- No data crossing with health professional diagnosis
- No diet information associated

9. **Fitbit** (https://www.fitbit.com/es)

It is a combination between a smartphone application and a tracker sensor to monitor the activity. It allows the establishment of daily objectives and long-term progress measuring the number of steps the user walks, the distance, the calories burned… It also allows the registration of the food you eat so as to register the number of calories you ingested and work with this information and the one provided by the sensor.

Advantages

- It combines information regarding diet and regarding exercise
- It uses additional sensors beyond the smartphone GPS
- It has smartphone application but the data can be also consulted with a PC
- It is available for iOS and Android
- The sensor is synchronized wireless with the smartphone or tablet



Disadvantages

- No data crossing with health professional diagnosis
- No recommendation engine based on the results

3.2 The Diabetes use case

3.2.1 Description of issue and how this is handled

Insert text

3.2.2 The MoSHCA solution for Diabetes

Insert text

3.2.3 Similar products for the Diabetes use case

There is **iBGStar** Diabetes Manager Application http://www.bgstar.com/web/ibgstar

It's a free smartphone application (for iPhone and iPod touch) developed by sanofi (French pharmaceutical industry) for diabetes type 1 and type 2 under insulin. This application is available in many languages (FR, NE, EN, GE, IT, ES)

The mains functionalities are a logbook organised based on the mealtime tags; an Insulin dose and carbohydrates consumption follow-up, Trend chart and statistics

It's connected to iBGstar (blood glucose meter that seamlessly connects to the Apple iPhone and iPod touch) to automated download of meter results

There are several applications about diabetes but another to be quote is **Diabéo** http://www.voluntis.com/en/therapeutic-solutions/diabeo.html

It's a telemedicine solution in development and clinical test are in progress. It's a Smartphone application for iOS and android for diabetes type 1 and type 2 under insulin Developed by Voluntis - sanofi and CERITD. This application is joined to a medical platform for doctors and nurses to see and follow up their patients.

3.3 The COPD use case

3.3.1 Description of issue and how this is handled

COPD is generally a progressive disease that is currently not curable, but largely preventable and with proper treatment, manageable. Exacerbations play an important role in the disease progression, have significant impact on patient wellbeing and determine for a large part COPD related health-care costs. Patients currently have regular but fairly sporadic contact with their physician unless there is an acute reason for an unscheduled visit. Exacerbation might go untreated for prolonged periods of times resulting in faster disease progression.

3.3.2 The MoSHCA solution for COPD

Objective:
Provide early detection of disease exacerbation through automated event detection, alerting, monitoring and treatment advice, as part of chronic disease management.

Benefit:
The chronic and progressive nature of COPD make a case for monitoring patients. This is especially relevant for the group of patients that have frequent exacerbations (acute events of worsening of symptoms). Important to note is that patients with frequent exacerbations usually have faster disease progression, which makes exacerbation prevention a particularly relevant goal. Monitoring for early

detection of exacerbations is paramount in providing treatment promptly. In addition, a faster treatment response to exacerbations leads to improved recovery and a better health status, and, if hospital admission can be prevented this benefits patients and reduces health-care cost.

Innovation:
Automated early detection of exacerbation to provide prompt treatment and manage disease progression.

3.3.3 Similar products for the COPD use case

One product that is relevant (at least in the Netherlands) is **MijnCOPDcoach** ("My COPD Coach").
https://www.mijncopdcoach.nl/

This application is more oriented to provide patient information and to organize their COPD management. The application is not primarily focused on preventing exacerbations, but there is a module where questions are asked to the patient, and an advice is given based on the "COPD Assessment Test" and "Clinical COPD Questionnaire". It does not make use of sensors and you have to use a website.

There is also a mobile device for COPD using the **Bosch Health Buddy**, see:
http://www.bosch-telehealth.com/en/us/products/health_buddy/health_buddy.html
http://www.ncbi.nlm.nih.gov/pubmed/18361703

In this approach, there are no real sensors attached to the device (you can only enter information, such as the blood pressure", which is sent to physicians/nurses), nor is there automatic interpretation of the data.

3.4 The (hypertension in) Pregnancy use case

3.4.1 Description of issue and how this is handled

Approximately 15% of first-time pregnant women develop part of this syndrome, characterized by high blood pressure and kidney damage with associated proteinuria (leakage of serum protein into the urine). It is the most important cause of death among pregnant women and a leading cause of fetal complications. The stage in pregnancy where high blood pressure develops is variable and associated problems can appear within days. This requires frequent outpatient checks for taking measurements, increasing the workload for the second- and third-line health-care centers. As a pregnancy-related condition the only way to cure preeclampsia is to deliver the baby. However, early anti-hypertensive treatment in the sub-clinical, mostly moderately hypertensive phase, reduces the risk of getting preeclampsia.

3.4.2 The MoSHCA solution for Hypertension during Pregnancy

Objective:
Preeclampsia prevention through timely detection.

Benefit:
Preeclampsia is a preventable disease. Timely detection allows closer monitoring of those patients at risk and gives the opportunity to start with preventive medication. Also, home measurements relieve the workload of health-care workers and their cost.

Innovation:
Smartphones provide sufficient computing power for offline decision-making support to detect symptoms leading to preeclampsia.

3.4.3 Similar products for the (hypertension in) Pregnancy use case

There is **BP@Home** - a home monitoring system for pressuring blood pressure and sending it to the care professional:
https://www.bpathome.com/main/pexperiences-movie.html

The main differences:

- Only 1 type of measurement (whereas in our case we have 4 measurements currently).
- No interpretation of the data, except that it alerts if the BP is above a certain threshold (140/90).
- They do not make use of risk factors.
- You have to use a website, instead of a mobile device.

There are also various apps for pregnancy. See:
http://www.mazecordblood.com/pregnancyappdirectory.php

For example "**BP tracker**" or "**Pregnancy Diary II**" are related. They typically provide information about pregnancy and allow you to keep track (log) information related to the pregnancy. Contrary to our use case, they do not really enable self-management or medical interpretation of the data.

3.5 The Hypertension Management use case

3.5.1 Description of issue and how this is handled

Blood pressure (BP) contrrol is a key factor to manage the hypertension. The use of telemedicine technologies and devices has been applied to help blood pressure control. However, many trials for the senior patients had failed on hypertension management by barriers like usability, trust and device costs.

The smartphone and mobile application resolve the exsisting barriers with trust and cost redcution. However, we still have problems for hypertension management.

- Data accuracy from a medical sensor – use Continua certificated medical sensor and develop averaging mechanism for the collected data
- Service prices and costs – plans to develop B2B model
- Limited use of standard protocol by a blood pressure meter - we could use a medical protocol converter for hypertension use case, so we can collect data from non-compliance devices.
- Legal issues for stored personal data – finding markets other contries like middle Asia and Africa

3.5.2 The MoSHCA solution for Hypertension Management

Objective:

The objetive of hypertension management application is provideing better understanding patient's blood pressure changes during general life for medical professionals and patients.

Benefit:

The hypertension is a chronic disease that manages whole lifetime. Furthermore, it is very closely related lifestyle of patients. Hypertension is a symptom of several cardiovascular and kidney diseases. This smartphone application gives some benefits on both medical professional and patient.

1. Easiness of blood pressure management

2. Patient-specific rules by medical professional

3. Better and accurate decision making for medical professionals

4. Minimize medication side effects and increase medication adherence

5. Intelligent decison making by patient lifestyle and social factors

6. Understanding of relevent factors for the hypertension

Innovation:

1. Using a medica standard protocol, the application can collect blood pressure data from various blood pressure meters in the market.

2. Consolidated blood pressure self-care management solution

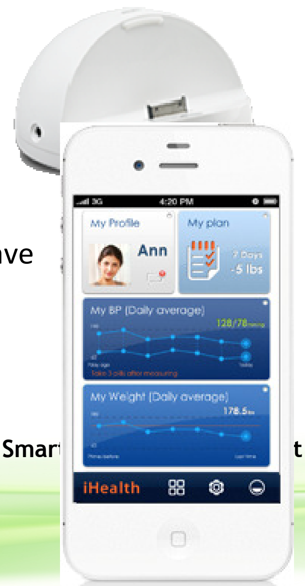
3. Defined rules for hypertension patients

4. Easiness of healthcare provider intervention and reminder

3.5.3 Similar products for the Hypertension management use case

For hypertension self-management, there are several products are available in the market. The most products support not only hypertension but also other telemedicine features.

iHealth – IOS docking device for blood pressure monitor
- http://www.ihealthlabs.fr/blood-pressure-doc-feature_31.htm



iHealth Tensionmeter BP3 is the connected blood pressure monitor device with IPhone and IOS application. The patients simply plug iPhone into BP3 dock and measure and monitor patient's blood pressure, heart rate, and pulse using iHealth App (MyVitals). The mobile App support following features:

- Measure and track your systolic / diastolic, your heart rate, pulse wave and the measurement time.

- Create dynamic charts to visually track your progress. Compare your results against historical averages, as well as against the classifications of the WHO
- Share your results instantly with your friends, family or your doctor
- Follow the effect of your physical activity and your daily diet as part of your overall health

The IHealth App MyVitals can customize the products you use such hypertension. Track your progress and manage patient's health in a more practical way without limitation.

HiCare – Telemedicine station, Home Medical Equipment, InSung Information (S. Korea)
- http://www.hicare.net/product_overview/

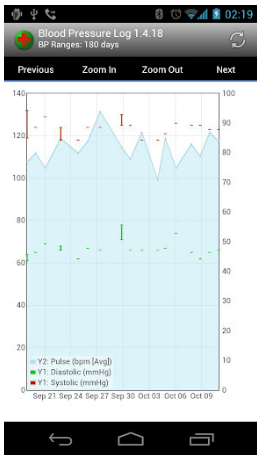
HiCare home doctor is a telemedicine device, which has activated interactive communication between an automatic electronic pressure meter and wireless medical devices through the external interface such as wire, and wireless, Bluetooth.

- Measure blood pressure and glucose
- Remote video consultation
- Multi-user support
- Multiple medical sensors data input with various wire/wireless interface
- Support medical standard IEEE/ISO 11703 and HL7 for data exchange
- Support a basic PHR and hospital HER, EMR information system
- Support various service model for healthcare providers

Blood Pressure Log – A&D Medical

http://www.andonline.com/medical/products/details.php?catname=&product_num=BP_Log_App_(Android)

A&D is the global leader of blood pressure manufacture and they released mobile Apps to monitor user's blood pressure with their products.



Blood Pressure Log will help users store and analyze patient's blood pressure, pulse in hospital or home.

- Unlimited users
- Data entry: Date, time, location, systolic and diastolic blood pressure, pulse, weight, and comments
- Support statistical data and visual chart analysis
- Data export to various format: CSV, XML, JSON, HTML, and Google documents
- Mobile platform: iOS, Android

3.6 The Mobility Rehabilitation use case

3.6.1 Description of issue and how this is handled

Fracture Rehabilitation

Patients that are rehabilitating after surgery or trauma related to one of their legs need to limit loading on the affected limb during the weeks of rehabilitation. An example is patients that are recovering after a hip fracture. These patients can help their rehabilitation significantly by adhering to the desired loading pattern properly. Current treatment consist out of testing the desired loading in a static situation on a weighting scale, followed by transferring the feeling of static loading into a dynamic loading during walking. For both the patient and the physiotherapist it is very difficult to notice whether the desired loading pattern is complied with and optimal rehabilitation duration is achieved.

Balance after stroke rehabilitation

Patients that are recovering after a stroke often have trouble with their balance – for many of these patients this means that they do not have full control over one of their legs. The current treatment of balance disturbances is not supported by mobile medical devices. It is mainly tests that are used to measure the balance level of the patient, in some of the larger rehabilitation centres expensive and time consuming walking robots or treadmills are being used.
If no supporting apparatus are being used the physiotherapists physically supports the patient during walking in the first stages of rehabilitation. For both the patient and the physiotherapist it is very difficult to notice and correct the balance distribution during these exercises.

3.6.2 The MoSHCA solution for Mobility Rehabilitation

Fracture Rehabilitation

Objective:
Providing loading data of one leg during and after carrying out exercises to support patient, physiotherapist and doctors in treatment and predict the recovery time of the patient.

Benefit:
Patients recovering from a leg fracture and their physiotherapists are given insight in the loading pattern on the leg of the patient in real-time and after the exercise. For the patient it takes away uncertainty by providing instantaneous feedback about the loading and it can speed up their rehabilitation significantly by adhering to the desired loading pattern. For the physiotherapist it gives insight in the patients actual loading, progress over time and expected recovery date based on the loading data.

Innovation:
Ambulant, wireless system that monitors the current status of the weight that is exerted on a leg of a patient and predicts the recovery time of this patient using a force sensor that does not need to be calibrated on the patient.

Balance after stroke rehabilitation

Objective:

Providing loading data of both legs during and after carrying out exercises to support patient, physiotherapist and doctors in treatment and predict the optimal balance state of the patient.

Benefit:
Patients recovering from stroke and their physiotherapists are given insight in the balance of the patient in real-time and after the exercise. For the patient it takes away uncertainty by providing instantaneous feedback about the balance and it can speed up their rehabilitation significantly by adhering to the desired loading pattern. For the physiotherapist it gives insight in the patients actual loading and balance, progress over time and expected recovery date based on the loading data.

Innovation:
Ambulant, wireless system that monitors the current status of the weight that is exerted on a leg and balance of a CVA patient and predicts the optimal state of this patient using force sensors that do not need to be calibrated on the patient.

3.6.3 Similar products for the Mobility Rehabilitation use case

In the current treatment of balance disturbances no device are used, it is mainly tests that are used to measure the balance level of the patient. There are however products that are comparable with the current SensiStep system which registers the axial loading under the heel and presents the data in a graph. Examples of these systems are the Xsens ForceShoe and PedAlert Monitor.

Xsens ForceShoe (http://www.xsens.com/en/general/forceshoe) fully ambulatory system for 3D measurement of forces and torques under the foot, as well as 3D kinematics of the foot. The system is wireless, real-time and replaces the weighting scale or build-in force plate. Xsens call the product is an ambulatory gait lab. In comparison with SensiStep the system is more advanced in measuring forces and toques, and the comparison (of the stride asymmetry) of two feet is already integrated. But at the same time the device is more expensive, designed from a technical perspective and not commercially available. Also the force sensors are build-in under a pair of heavy shoes, available in one shoe size, which are via a wire connected to a data sending device. This makes the system only semi-wireless and less flexible. To read out the data of the Xsens ForceShoe, a specific software package is needed which runs on a pc of laptop. Only the health care professional or investigator will get direct feedback from the system.

The **PedAlert Monitor** (http://www.activeforever.com/pedalert-monitor) is a device that monitors the amount of weight put on the lower limb and sounds an alert when the threshold is close. The PedAlert Monitor rests on a cast shoe which the patient wears over their normal shoes, cast, or foot. The sensor is integrated in the cast shoe and connected to the PedAlert Monitor via a wire.
The graceless PedAlert shoe comes in one size, uses maximum weight only, has to be calibrated individually for every patient. Thereby the system is not wireless, gives only feedback for the patient, gives only feedback about overloading not about under loading, Next to that the system is not very user friendly as it gives feedback only via sound about reaching the threshold, disconnection and about low battery power.

The **OrthoSensor** kneebalancer (http://www.orthosensor.com/orthosensor) is an invasive disposable instrument which can enhance clinical outcomes in orthopedic surgery. The instrument can be placed in the knee joint to monitor both soft tissue balancing and alignment of the knee prosthesis. The OrthoSensor sends the data wireless and real-time into the cloud and the software will process the data to simulate the balance and alignment, but also to give early warning signs of implant failure, bone degradation and other musculoskeletal analytics. The data is accessible via a web portal and can be integrated in electronic medical

records , personal health records, enterprise resource planning and disease management systems. The instrument does not change the workflow of the surgeon.
If this instrument would be used instead of SensiStep, a big disadvantage would be that it is an invasive instrument and an invasive procedure to implement, an advantage would be that the patient can be monitored at any time as the instrument is carried along automatically.

Next to these examples the University of Utah is developing a **smart insole** which might become a real competitor in weight bearing measurements. This product is still in development phases, therefore a good comparison cannot be made yet.

3.7 The Baby Monitoring use case

3.7.1 Description of issue and how this is handled

Prematurely born babies usually need special medical attention in the neonatal intensive care unit until their systems and organs can function without any external assistance. Recent studies show that during part of this time the baby needs only supervision rather than medical treatment and that this time is shorter if spent in a familiar and loving environment. Some health centres allow the parents to take the baby home, however, complications might arise at any time and therefore babies still have to receive periodic visits by a nurse.

3.7.2 The MoSHCA solution for Baby Monitoring

Objective:
The purpose of this solution is the monitoring and control at home of babies born with low weight via a smartphone. The caregivers, usually the babies' parents, will collect regularly measurements and other data on the baby. This information will be transmitted to a server, where the doctors can perform a close monitoring of the baby progress.

Benefit:
Spending the minimal medical care period at home not only benefits the baby (a baby at home it is believed to make a sooner recovery), but also the families, the doctors and the medical centre's budgets. Families can return home earlier, which helps them to cope with the emotional distress associated with the uncertainty of their baby's future in the period immediately following the birth. Doctors can easily check the information submitted by the parents anytime and anywhere in order to assess the proper evolution of the baby whilst having direct communication with the baby's family. Finally, hospitals can save a considerable amount of money since there is less need for infrastructure (also the personnel can attend other patients).

Innovation:
1. Integration with wireless devices to make easier and more errorless the taking of measurements.
2. Local and global reasoning modules that can give advices to caregivers and trigger alarms in little time.
3. Adaptation to the caregivers and doctors' available schedules, implying stress reduction. Doctors can usually choose the time of day for browsing the MoSHCA web site; this allows doctors to treat several patients without time pauses. Caregivers can use the smartphone application in a more flexible way, according to the patient needs (at least one time per day or regularly in accordance to a suitable pre-programmed plan).

3.7.3 Similar products for the Baby Monitoring use case

Baby Insights Day tracker: Babblesoft developed a cell phone application for parents to use as a diary for their baby daily routine. By having the information regarding sleep periods, breastfeeding times, bottle feeding times and amounts, pumping times and amounts, immunizations and medicine doses and diaper changes stored in a virtual place accessible for parents, nannies, doctors or any other person who takes care of the baby, babblesoft intended to give new parents a better insight into their baby's patterns to improve the care and communication among different possible carers. This project was a great idea that helped parents takes care in a more effective manner of their healthy infant. However, in the case of not healthy babies doctor involvement needs to be deeper. This application was deprecated.

MOBI-NIÑOS: Answare Tech in close cooperation with the Spanish hospital of Puerta Del Hierro in Fuenlabrada developed a telemedicine system to promote the early release of babies born with low weight. This project was conceived as part of the Spanish national plan for scientific research or Plan Nacional de Investigación Científica, Desarrollo e Innovación Tecnológica (2008-2011), Plan Avanza and Plan Ingenio 2010.
Following the doctors criteria Answare Tech designed a system to let doctors follow up on these patients remotely favouring a sooner recovery. This project involves the parents of the patients who need to measure and monitor their babies' vitals and then input them in a smart phone. Information is submitted over the internet and stored on a server where the doctor can review it and act accordingly. Opposite to the MoSCHA applications for premature babies, parents need to insert manually every parameter, whereas with MoSHCA, reading of some of these parameters is automatic, which increases the accuracy of the data.

Petits a casa: Sant Pau's hospital, from Barcelona, developed a web portal in order to improve the monitoring of discharged babies born with a low weight. In such portal parents are asked to answer different questions regarding the baby's status in a periodic way. This questionnaire is later evaluated by caregivers and nurses from the hospital who can perform an evaluation of the cuddle, can ask parents to take actions and can give advice to inexperienced parents. Petits a casa proved to improve the babies' monitoring and to promote a higher involvement of parents in their baby's care. Nevertheless, Petits a casa only acted as a communication tool between parents and the paediatrics unit, it did not take benefit of the advantages that smartphones and wireless sensors offers (obtaining accurate measurements in an easy and practical way) nor used any reasoning component in order to automatically asses the baby's situation.

Project Artemis: Project Artemis (see html link) is a collaborative initiative involving Toronto's Hospital for Sick Children, the University of Ontario Institute of Technology (UOIT) in Oshawa, Ont., and IBM Canada. The goal of the project is to capture and analyze vast amounts of physiological data from premature babies and then present that information to physicians and nurses.

Crimson Tide (see html link) has delivered a world class mobile nursing solution. Crimson Tide's client employs a number of nurses who visit homes to monitor the health of prematurely born babies. Many home-born or hospital-born premature babies need continued monitoring when they are at home. Nurses record critical readings such as temperature and blood pressure and can also administer drugs to the baby during their visit.

3.8 The Epilepsy Detection use case

3.8.1 Description of issue and how this is handled

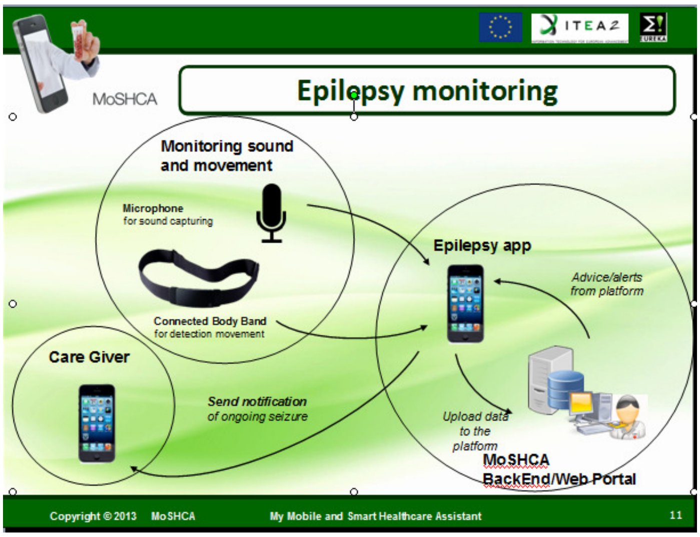
Patient suffering from epileptic seizures now need permanent supervision of a care giver to ensure that seizures are detected and treated at early stage to prevent health damage or ends fatal. Having someone around 24/7 is an enormous invasion of the patient privacy as well as a heavy burden on care givers. Cases where parents for years take turns to sleep in with a child suffering from epileptic seizures are not uncommon.

3.8.2 The MoSHCA solution for Epilepsy Detection

Objective:
Mobile detection of epileptic seizures allowing patient more freedom and privacy whilst enabling alert response by caregivers.

Benefit:
Patient suffering from epileptic seizures no longer need permanent supervision from care givers. This will significantly improve the patients privacy and increase the feeling of being able to function independently . The stress and burden on care givers and such as parents can be relieved without compromising patient safety.

Innovation:
Recognition of epileptic seizure using acoustic monitoring.



3.8.3 Similar products for the Epilepsy detection use case

Epilepsy Detector Application: **Epdetect**
http://www.epdetect.com/index.html

Epdetect is an accelerometer based mobile phone application that uses advanced signal processing to

detect epileptic seizures. It runs on most mobile phones that support SMS messaging, movement detection and GPS position location.
The addition of the seizure detection signal processing enables the phone to function as a wearable seizure detection system, with remote signalling to carers. Epdetect monitors the wearers movements, distinguishing between normal movement and movement associated with a Tonic–clonic seizure. If a seizure is detected, Epdetect will contact and alert your carer with your status and GPS position.

Polish mobile app will increase the safety of epileptics
http://www.nauka.gov.pl/scientific-research/polish-science/science/science/artykul/polish-mobile-app-will-increase-the-safety-of-epileptics/

It will tell bystanders how to help a person in an epileptic seizure and notifies the person's family of the location. The application, which will increase the safety of epileptics, has been developed by scientists and students of the Military University of Technology.
Part of the application is a sensor EMG that monitors muscle activity. Sensor can be attached to any muscle group, such as thighs, chest, back or shoulders. Its size is similar to a cell phone battery. The system detects so-called tonic-clonic seizures, usually manifested by convulsions and loss of consciousness. "Our sensor will transmit information of such muscular activity wirelessly to a cell phone, which will analyse the signal and decide on further action" - said Dr. Mariusz Chmielewski in an interview with PAP.
"We are building algorithms that learn muscle activity patterns typical of tonic-clonic seizures. This allows our algorithm to +know+ how to distinguish between dangerous situations and false alarms"...
"We get a lot of calls from people who want buy our application, but for now we cannot sell it for procedural reasons. Medical device market is very different from general consumer solutions. We want to avoid a situation in which the solution is inaccurate, therefore we need research and clinical trials that cost a lot" - said the scientist.

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[i] https://www.bluetooth.org/en-us/specification/adopted-specifications
[ii] Continua Health Alliance : www.ContinuaAlliance.org
[iii] Scully, C. G., Lee, J., Meyer, J., Gorbach, A. M., Granquist-Fraser, D., Mendelson, Y., & Chon, K. H. (2012). Physiological parameter monitoring from optical recordings with a mobile phone. Biomedical Engineering, IEEE Transactions on, 59(2), 303-306.