Challenges and opportunities from the use of biosensors and IoT in smart healthcare applications

Maria Pateraki[1], Konstantinos Fysarakis[2], Vangelis Sakkalis[1], Georgios Spanoudakis[2], Iraklis Varlamis[1,3], Michail Maniadakis[1], Manolis Lourakis[1], Sotiris Ioannidis[1], Nicholas Cummins[4], Björn Schuller[4], Evangelos Loutsetis[1], Dimitrios Koutsouris[5]

[1]Institute of Computer Science, Foundation for Research and Technology – Hellas, Greece
[2]Sphynx Technology Solutions AG, Zug, Switzerland
[3]Department of Informatics and Telematics, Harokopio University of Athens, Greece
[4]ZD.B Chair of Embedded Intelligence for Health Care and Wellness, University of Augsburg, Germany
[5]Institute of Communication and Computer Systems, Athens, Greece

Abstract:

The use of health and well-being monitoring technologies has been steadily increasing and such systems can nowadays be found in smart homes, age-friendly workplaces, public spaces and elsewhere. They deploy a wide variety of off-the-shelf smart sensors and medical devices to support functional, physiological and behavioral monitoring, address social interaction aspects of daily life, and focus either on specific health-related conditions or on supporting the more general aim of comfort, well-being and quality of life. However, there are still several technological (interoperability, expandability, etc.) and societal (cost privacy, etc.) challenges to be addressed before smart biosensor systems are widely adopted.

Motivated by the above, this chapter highlights the challenges and opportunities from the application of smart biosensors in healthcare and presents three state-of-the-art solutions leveraging smart sensors in this context. The first concerns ***a smart living solution platform*** that integrates heterogeneous sensors and assistive medical and mobile devices, enabling continuous data collection from the everyday life of the elderly and data analytics that support personalized interventions. The second presents ***an IoT ecosystem*** comprising sensors and smart wearables to improve occupational safety and workforce productivity through personalized recommendations. The last case is ***an intelligent non-invasive bio-signal recording system*** that detects potentially hazardous pathological conditions of infants during sleep.

1. Introduction

As global population is ageing, several disorders, diseases and impairments are becoming prevalent with significant financial and social implications. The prevention and appropriate handling of such conditions will be beneficial both for the individuals and the national healthcare systems. Smart ICT solutions can provide benefits such as improving the quality of live and supporting the independent living of the elderly.

Biosensors are complete analytical devices, where the receptor, an active biological system that can be an enzyme, an antibody or similar, is placed on top of a transducer and is able to detect the existence of a particular analyte. They are a continuous source of biological data and when integrated in a smart analytics framework, they can provide useful information about a person's condition. Smart biosensors in health capitalize on recent advances in micro-technology and wireless communication in order to collect and transmit information and, in conjunction with actuators, are able to provide better monitoring and treatment. For example, wearable biosensors provide vital signs monitoring for everyone, from patients to children and the elderly, and are very effective in health risk prevention and control.

The use of smart biosensors can be beneficial for people that require medical support or care, as well as for older adults, who face a gradual degradation of their motor, cognitive and other skills due to ageing. It can also be of help to people who are exposed in harsh working environments, perform stressful tasks or tasks that induce health risks. The continuous monitoring of bio-signals in combination with environmental sensing allows smart systems to promote a reactive living and working environment, which provides appropriate and timed recommendations, acts preventively and mitigates health risks.

The long list of biosensor applications (Mehrotra, 2016; Ajami & Teimouri, 2015) includes, among others, wearable helmets for treating depression through electrical pulses, smart clothes (from socks and shoes to t-shirts and smart vests) that non-invasively collect and transmit vital signs and integrate well with the concept of a smart house or a smart working environment (Cham et al., 2012).

2. The health challenges for the elderly, older workers and infants

According to HelpAge International[1], by the year 2050, one in five people will be over 60. Amongst the ten most prevalent health challenges that lead elderly people to physical injuries and affect their ability to have a healthy and independent living (WHO, 2015) are the following:

- **Hearing Loss (HL):** It is one of the top prevalent chronic conditions for older adults (Vos et al., 2017), that affects one third of people aged between 65 and 74, and nearly half of those older than 75. Increases the risk of cognitive decline and depression, and can lead to social isolation.
- **Cardiovascular Diseases (CVDs):** Hypertension, ischemic heart disease and heart failure are the primary cause of death globally (31% in 2016, 85% of which from ischemic heart disease and stroke) (WHO, 2017). They affect many aspects of the life of elder adults including their physical, social, and emotional status.
- **Cognitive Impairments (CI):** They affect the ability of people to think, learn and remember. Dementia is the most common issues with approximately 47.5 million cases worldwide and a prediction to triple by 2050. It has high comorbidity with heart failure among the elderly, and affects several cognitive domains including executive and motor function (Leto & Feola, 2014).
- **Mental Health issues (MH):** They affect an important ratio of the older population (e.g. depression at 7%, anxiety disorders at 3.8%, substance use problems at almost 1%, self-harm attempts are the reason behind 25% of elderly deaths) and in some cases have an impact on the physical health. Also, adults with a bad health condition (e.g. heart disease) have a higher risk for MH issues.
- **Balance Disorders (BD):** Balance disorders are disturbances in coordination that make someone feel unsteady, dizzy or have a sensation of movement. This age-related progressive loss of functioning of sensory information and inability to control body movements frequently lead to falls, physical injury and death (one elderly person dies from falling every 29 minutes (EIPAHA, 2012)). Frailty is

[1] www.helpage.org/resources/ageing-data/global-ageing-statistics/

quite prevalent among elderly people (the ratio ranges between 33% to 88% depending on how frailty is defined and steadily increases with age). Frailty and more accumulated disorders increase the risk for the elderly and negatively affect their quality of life (Murad & Kitzman, 2012).

Since health problems increase with age, and the age limits for retirement keep increasing, more employees are likely to develop health problems while still at work. Changes in physical abilities (e.g. balance, mobility, dexterity, stature, strength and aerobic power) can result in a reduced tolerance of physical work and declines in motor skills (e.g. difficulty to maintain coordination, loss of flexibility, etc.) render tasks that require fine manipulation harder for older workers. Finally, changes in cognitive abilities (e.g. episodic memory, declines in executive functioning and attentional control) reduce task performance and affect work capacity (Jekel et al, 2015). Vice versa, cumulative exposure to demanding work can have a significant impact on health and functional abilities, wellness in work and productivity. Arduous working conditions (e.g. exposure to extreme temperatures, dangerous substances or noise) have a major influence on the risk of developing work-related ill-health (illness, stress, fatigue, etc.). When the work environments require workers to exert intense physical effort, even occasionally, it is important to keep workers safe and healthy so as to increase their resilience and avoid injury risks (Chowhan et al, 2019).

On the opposite end of the age scale, various pathological conditions can arise during the first year of the life of infants, which call for immediate detection and intervention, considering that parents cannot always identify the signs of pathology that specific movements and sounds of an infant indicate. According to WHO[2] a child is at the highest risk of dying in the first 28 days of life, while at home; especially when neonates are early discharged from the hospital. Current countermeasures include postnatal care plans built around home visits of healthcare professionals. Many pathological situations can occur during an infant's night sleep that can potentially be harmful to health if not detected promptly: breathing disorders, vomiting, arrhythmias, epileptic and febrile convulsions, high fever and sleep

[2] https://www.who.int/news-room/fact-sheets/detail/newborns-reducing-mortality

disorders (ranked in order of life threatening risk), including sudden infant death syndrome.

3. Challenges and opportunities for technology-enabled care

3.1. Low-cost technology

The explosive growth of the Internet of things (IoT) and associated technology put a downward pressure to the cost of the associated hardware and software (Mehrotra 2016). Building successful low-cost technology-enabled care (TEC) solutions depends on a number of factors that either relate i) to sensors that must have: a) low power consumption for prolonging battery life; b) physical characteristics that provide unobtrusiveness; c) robustness to minimize maintenance; d) wireless connectivity to facilitate networking using widely accepted standards and e) data pre-processing capabilities to reduce computational load on gateways and cloud or ii) to the network itself which must support: a) the deployment and management of a large number of low cost sensors; b) high processing speed and portability to enable better care at lower cost.

3.2. Modular, interoperable, expandable solution

Realistic and usable IoT applications will require the interconnection and networking of large numbers of heterogeneous smart objects and IoT solutions, covering different communication technologies (Bluetooth, RFID, Zigbee, 802.11, 802.15.4 etc.), running a variety of often proprietary protocols and applications, with limited exposed interfaces (Razzaque et al., 2016). Many surveys highlight that vendor lock-in and complicated security and manageability processes hinder the broader adoption of IoT technologies (Brush et al., 2011). Aiming to alleviate the interoperability issues, various IoT platforms are emerging, either domain-specific (e.g. UniversAAL[3]) or general-purpose ones (e.g. FI-WARE[4], GoogleApp engine[5]). Thus, developers rely on existing platforms and their services, and future platforms

[3] http://www.universaal.info
[4] http://www.fi-ware.org
[5] https://cloud.google.com/appengine/

must be interoperable with the existing ones. Moreover, various standardized "IoT communication protocols" have been proposed, aiming to address the interoperability and fragmentation issues. The MQ Telemetry Transport (MQTT[6]) is one such machine-to-machine (M2M) connectivity protocol, recently standardized by OASIS (also standardized as ISO/IEC 20922), and already applied in various domains that include eHealth (Gomes et al., 2015) and smart homes (Kim at al., 2015). The OASIS standard DPWS (Driscoll et. al., 2009), supports the interaction with resource-constrained devices and has been studied extensively in many areas, including eHealth and smart homes (Fysarakis et al, 2014). The IETF standard CoAP (Shelby et al, 2014), offers an alternative web transfer protocol, which allows the integration of constrained IoT nodes through lightweight interactions.

3.3. Big data and machine learning

With environmental sensors and wearable devices, smart healthcare platforms can continuously monitor the health status and activities of the patients and/or elderly, and the safety and security of the environment. This continuous flow of data in combination with people's medical history, can support personalized diagnosis and assistance and automate important tasks, such as medical data archiving and the evaluation of medical interventions effectiveness. Recent advances in artificial intelligence and big data processing technologies have allowed the implementation of highly reliable, accurate and robust infrastructures data recording and processing (Da Cruz et al., 2018). The analysis of such data can be led by the decision making process requirements, which define the data to be collected and evidence to be extracted for supporting intelligent decision making. To support this, the following requirements must be considered: i) modular and interoperable data ingestion, in which devices from different manufacturers contribute to a common data model, ii) parallelization and data stream processing in all steps from data acquisition to storage and processing, iii) use of data analytics and artificial intelligence, to support automatic monitoring and decision making, iv) privacy-aware data processing, to

---

[6] https://docs.oasis-open.org/mqtt/mqtt/v5.0/mqtt-v5.0.html

ensure consistent data encryption, database security, as well as secured communication channels.

3.4. Security and privacy

The complex interaction schemes that take place during typical, everyday use of smart healthcare solutions (e.g. patients/users with their caregivers/medical professionals, etc), along with the private/sensitive nature of the handled data, necessitate the integration of strong security and privacy provisions, including seamless authentication and authorization services, for the protection of the framework's Machine-to-Machine (M2M) and Machine-to-Human (M2H) interactions (Da Cruz et al., 2018). IoT devices have been designed mainly considering low cost, low energy usage, ease of set-up, use and interconnection and not security. Since health monitoring systems or even smart homes and workplaces may include sensitive assets, it is important to protect them from malicious attackers.

The above define a set of security and privacy risks that must be considered:

- Small, low cost, interconnected devices have immature security functions.
- Low processing capabilities of the network require computationally intensive real-time tasks (e.g. condition reasoning) to be moved to the cloud.
- Secure communication within the smart home, use a range of protocols (WiFi, Bluetooth, NFC, ZigBee and others), that may open various exploits.
- Privacy protection systems (e.g. smart home sensors) generate a large amount of highly personal data and metadata.
- Consent for secure sharing of anonymised information is necessary.
- The physical security of a smart home is linked to the safety of sensitive systems for the occupants' healthcare.
- Secure communications with the backend processing systems.
- Secure and privacy–preserving interactions (communication, processing, storage) with third parties (hospitals, clinics, etc), their data and metadata.
- Authentication, authorization and accounting mechanisms must be tailored to all actors (from elderly and clinical experts to sensors and backend systems).

- Reliability and availability of information from back-end databases and real time data streams must be guaranteed.

The information sources to be protected encompass data from smart devices, including raw data, logs, metadata (headers, content type, dates, etc.), events (alerts, warnings, errors, etc.), rules, settings and preferences (which may disclose information about the end user's conditions), updates to and from smart devices, post-processed data and interactions of the smart home with the backend cloud, as well as interactions of the latter with the various healthcare service providers. All adopted security and privacy mechanisms will have to be tailored to the above requirements, and a key characteristic will be their capability to adapt in real-time to a variety of usage requirements (e.g. context, privacy preferences, risk profile and other parameters).

4. IoT and IoMT building blocks for health and wellbeing applications

4.1. Smart environment enablers

4.1.1. Wearable and assistive medical devices

A basic component of a smart solution for health is a wireless sensor network obtaining automated, continuous, and real-time measurements of physiological signals and performing limited data processing and functions. Vital signs, such as heart rate, heart rate variability, body temperature, skin conductance, respiration rate, blood pressure, blood glucose, oxygen saturation, as well as activity related signals can be captured and analysed using appropriately selected sensors that can be placed over clothes or directly on the body. Other physiological measurements that can be recorded is hearing response, where hearing aids contribute to. The current state of the art of the aforementioned sensors indicates the lack of multi-parameter systems for the concurrent monitoring of the physiological measurements. On the other hand, the utilization of separate sensors is not practical and may cause inconvenience and obtrusive operation for the end users.

The human body physiological signs can be measured with different sensor technologies (Jeong et al., 2019), some of which are depicted in **Table 1**. The heart rate, which has become a routine measurement, can be easily extracted from PPG (photoplethysmography) signals. Blood pressure derives from inflatable cuffs accompanied with a stethoscope. The evolution of this medical device resulted in an integrated smart pressure sensor (Dias and Paulo Silva, 2018). Moreover, blood oxygen saturation, a valuable vital parameter, can nowadays be easily measured through the exploitation of PPG technology. PPG is a biophotonic technology using two different light wavelengths (Mendelson et al., 2013). The basic type of sensors in skin sweat monitoring are epidermal galvanic skin response (GSR) sensors. Also the respiration rate is used to detect stress and potential hypoxia (Xiao-Fei et al., 2008).

Table 1. Physiological measurement solutions in the IoT era

Physiological measurement	Sensor type	Data provided
Heart rate	PPG	Raw
Blood pressure	Pressure sensor	Raw
Blood glucose	POC	Raw
Respiration rate	Sensitive stretch sensor	Raw
Oxygen saturation	PPG	Raw
Body temperature	Thermocouple	Raw
Skin conductance and temperature	GSR	Raw
Activity	IMU	Raw, aggregated
Sympathetic nervous system activity	GSR	Raw
Hearing response	-	Raw, aggregated

More recently, wearable devices that can infer the human physical activity have gained high popularity. Such devices often incorporate IMU, GPS, PPG sensors, ECG leads and sophisticated firmware capable of high quality and continuous biosignal monitoring (Henriksen et al., 2018). Finally, sympathetic nervous system activity can be captured using electrodermal activity (EDA) sensors which offer information about alterations in the central nervous system. Assessment of these alterations leads to indicators of the emotional condition of the subjects (Zangróniz et al., 2017). The abovementioned sensors can be integrated in wearable devices specifically designed to extract raw, aggregated or both types of data and collectively compose a smart IoT ecosystem.

Considering the above landscape, a smart healthcare solution must be able to integrate physiological measurements, such as those reported above, aggregate (also pre-processing them, if necessary), and transmit them to a backend cloud platform where huge amounts of raw and aggregated data can be analysed through advanced big data analytics to elicit behavioural activity, detect probable risks and provide the adequate interventions.

4.1.2. Mobile devices

Mobile devices are an integral part of smart healthcare solutions. They are the near perfect interface to actively gather self-reported data from individuals. Additionally, they contain a vast array of embedded sensors and features for collecting a large variety of data, both actively and passively, which can be used to infer information regarding a subject's current health or mental state. Behavioural signals such as speech, facial expression, and gaze can also be collected through the cameras and microphones embedded in all consumer smartphones and tablets. Furthermore, mobile devices offer temporary storage and the means to remotely transmit this information. They also represent a straightforward solution for the intermediary storage of health and wellness data collected from wearable and other IoT devices before transmission to a backend cloud platform for analysis (Khan et al., 2013). However, as already pointed out in the previous section, this transmission represents a potential security risk and can quickly drain the limited power available to these devices. In addition to functioning as storage, transmission and potentially processing devices, smartphones represent a new source of health and wellness information. In particular, the shift to mobile devices, smartphones and tablets as a core communication platform, has resulted in a new source of data known as digital-trace information. This data stream is generated implicitly through smartphone usage and can be collected passively and unobtrusively (without specific user interaction) by the use of specially designed apps. One such app is RADAR-BASE, which runs as a background process which automatically collects and transmits this information for analysis and predictive monitoring (Ranjan et al., 2018). Implicit trace information gathered from smartphones includes social activities as monitored via call and message logs, social media usage or Bluetooth connectivity; activity levels as inferred from embedded sensors or *Global Positioning Systems* (GPS) data.

Ambient noise and light levels, screen time, application usage can also be easily collected.

A growing area of research in smart healthcare solutions is the embedding of Artificial Intelligence (AI) technologies directly into mobile devices. However, considering that a modern deep neural network can have parameter numbers measuring in the millions, the computational demands associated with these technologies are very high, potentially requiring hundreds of megabytes and creating substantial data movement operation to support their operation; this a highly non-trivial process. One growing research direction within neural networks is the development of approaches which can import large networks and optimise them until they are executable on a low resource smart device (Frankle and Carbin 2018). Other methods are aimed at lowering the memory footprint and computational complexity of AI technologies while maintaining reasonable accuracy. Developing low resource networks increases the likelihood of smart systems being able to run offline, increasing user privacy and reducing energy consumption concerns associated with transmission bandwidth, all of these being core considerations for a robust smart healthcare solution.

4.1.3. Environmental monitoring and IoT platforms

Environmental monitoring encompasses a broad variety of IoT applications that involve online monitoring of environmental parameters such as temperature, humidity, noise levels, air pollutant concentrations, etc, that affect people's safety and well-being (Kumar et al., 2013). The measured parameters are collected through dedicated gateways by an IoT platform for monitoring and analytics.

The most popular IoT platforms for use as secure gateways are AGILE IoT, Eclipse Kura and HomeAssistant[7]. They are open source and feature ready-to-use field protocols, supporting wireless and wired IoT networking technologies such as WiFi, Bluetooth Low Energy (BLE), ZigBee, Z-Wave, etc. Recent promising results set the BLE suitable for adding power harvesting elements and mobile gateways using different types of wide-area networks, encouraging the development of systems

[7] http://agile-iot.eu, https://www.eclipse.org/kura and https://www.home-assistant.io

based on this technology (Mois et al. 2017). For publishing data and events to IoT cloud platforms, MQTT connectivity is an option available to all platforms. Every platform uses its own authentication system (OAuth2, multi factor authentication, etc.) for secure access, HTTP SSL/TLS protocols and MQTT connectivity securing the privacy of established connections.

AGILE IoT builds a modular and adaptive gateway for IoT devices that supports interoperability of devices and data. Modular hardware solutions that adopt all communication protocols in combination with the appropriate software components that offer smart services (data management on the gateway, intuitive interface for device management, etc) allow fast prototyping of extensible solutions. Eclipse Kura is an extensible open source IoT Edge Framework that offers API access to the IoT gateways (I2C, GPS, GPIOs, serial ports, etc.). HomeAssistant is an open source IoT platform with hundreds of built-in components for connectivity with off-the-shelf sensors, an easy framework for importing more devices and a mobile-friendly interface for setting up automation rules and monitoring devices.

4.1.4. Camera-based monitoring of humans

Despite not yet being widely adopted in IoT frameworks, visual sensing using cameras has several attractive advantages over other sensing modalities. These stem from the fact that visual sensing can support the extraction of detailed context information from a scene, while being passive, low-cost and non-intrusive. Context-awareness facilitates a better understanding of the activities/actions, health and risks faced by a subject being monitored by detecting behaviour patterns and supporting more precise inferences about the subject’s situation and their environment. Many systems rely by design on the extraction of low-level context information, such as the location of users, derived by non-visual sensors and technologies. However, in cases with more elaborate monitoring requirements, for example when one needs to extract higher-level information such as behavioral patterns and the subject’s activity, or when the environment is occupied by multiple persons or contains certain materials such as metal parts that may interfere with localization radio signals, visual information from camera sensors can provide richer and more precise information. However, in an IoT camera-based monitoring system, there are security and privacy risks that relate to the transmission of images away from the imaging sensor for processing, therefore it is preferred to move the application of security and privacy protection closer to the sensor, enabling an enhanced control of data privacy and, at the same time, accommodate key concerns among users regarding privacy violations.

Beyond the privacy issues, considering that human behaviour in daily activities is complex and highly diverse, monitoring such activities presents significant challenges. As outlined in (Kim et al., 2010) these are: a) recognizing concurrent activities: performing several activities simultaneously, b) recognizing interleaved activities: activities that are overlapped with others, c) ambiguity of interpretation: similar actions may be interpreted differently depending on the context, and d) support of multiple users: recognize the activities performed in parallel by many users in a group. Human behavior is characterised by varying time frames and levels of semantics (Chaaraoui et al., 2012). In addition to the above, robustness to variations in real-world indoor and outdoor environments is affected by scene- and image-dependent factors, such as variations in the performance of actions, background clutter, occlusions, lighting conditions, camera sensor selection and placement (Poppe, 2010).

With the advent of low-cost, real-time dense depth cameras such as the Kinect[8], numerous important approaches to the action recognition and tracking problems have emerged, pushing the state of the art significantly forward (Shotton et al., 2013). Nevertheless, and despite the fairly accurate performance of state-of-the-art algorithms in controlled or semi-controlled settings, coping with complex, realistic scenarios expose their limits especially handling effectively longer duration occlusions, which is an unsolved problem in most state-of-the-art approaches (Sigalas et al., 2016). Lastly, such approaches suffer from natural light interference and limited range, hence are restricted to indoor environments. On the other hand, passive stereo cameras have a wider range of application, as they can operate in sunlight and their field of view can be adjusted by using different cameras, lenses or baselines.

---

[8] https://www.xbox.com/en-US/kinect

Apart from spatial ambiguities related to human body segmentation in complex scenes, ambiguities in the temporal domain may also affect action recognition. These are easily resolved with repetitive actions, but they may greatly affect the detection of non-repetitive actions such as pulling, pushing or lifting an object. Moreover, performance may degrade in case of domain shift problems, for instance when the scale and shape of the human action are inconsistent with those of training data. Empirical results suggest (Feichtenhofer et al., 2016) that CNN-based algorithms are able to learn similar features between different actors performing the same action (i.e., performance nuance). However, in many real-world problems (e.g. surveillance scenarios), it is not possible to provide massive amounts of training data nor avail enough time for training. Thus, there is a need for algorithms which can work reliably in real-time with moderate amounts of data that will progressively improve their confidence as more data is learned, most desirably in an unsupervised fashion.

4.2. Backend enablers for personalized recommendations

4.2.1. Knowledge abstraction for user profiling and temporal reasoning

In order to reduce the predictable acute health episodes, a system should focus on eliminating complications, preventive disease management, and timely detection of anomalies based on past events. However, a characteristic of ordinary computerized health-care systems is the limitation of user participation to the decisions of the system. User-centered design has been recently adopted as a methodological tool to inform the development of modern health technology systems. Capitalizing on the use of IoT technologies and analytics, modern systems are able to infer hidden patient information and their-own risk-related parameters. The constant monitoring of incoming data can be used to trigger warnings on the identification or prediction of user-independent abnormal parameter values, or the identification of crucial deviations from a patient's data profile which may indicate the increase of a risk. Moreover, the exploitation of past data is important for the delivery of personalized treatment based on predictive modelling techniques that will determine the expected treatment response for a certain patient. Still, the comparison between past and current data which are frequently stored in the form of time series is not straightforward. Accordingly, it is often required to develop abstracted pictures of current and past events which are contrasted to reveal abnormalities. Dimensionality reduction is commonly used as an approach to develop simplified representations of the different cases (data sequences) and similarity-based comparisons between them to support time series retrieval and decision making (Moerchen, 2006). In recent years, temporal abstractions (TA) have been used as a method to derive high level concepts from time stamped data (Stacey & McGregor, 2007). The idea behind TA is to move from a point-based to an interval-based representation of data, which effectively summarizes the data into meaningful parts that are interpretable by the users of the system (Madkour et al., 2016). The evidence arising from the comparison of different cases is fed into decision models to identify and suggest interventions that either prevent the occurrence of risks or reduce their effect on patient health.

The use of big data analytics and the ease of aggregating and synthesizing anonymous patient clinical records facilitates the creation of custom cohorts and metrics to extract knowledge that can be transferable and applicable across different patients and can be used as a valuable service to third parties (Raghupathi & Raghupathi, 2014). Interestingly, besides building accurate models of disease progression and providing personalized medicine in clinical practice, big data analytics facilitates the integration of medical data with wearable devices and IoT smart sensors that provide information on supplementary behavioral determinants of health and may crucially support the analysis of potential public health policies at regional, national and international levels regarding such interventions (Vayena et al, 2018).

4.2.2. Context-aware recommendations

The most interactive part of a smart medical care solution based on biosensors emerges when the system recommends actions to the end user based on the information collected by the sensor ecosystem. When developing a recommender system for a specific purpose, such as the improvement of physical or mental status, it is important to consider what actions to recommend and at which moment they should be addressed to the user. This defines the concept of context-aware recommendation systems (CARS), which take into account the user spatio-temporal environment, as well as other conditions such as the user status (standing, walking, driving) or physical (tired or energetic) and psychological conditions (happy or sad). Sensors can be used to detect the user context (Ilarri et al, 2015) and be the backbone of CARS that support health and medical care. For example, in Casino et al (2017), authors propose a context aware recommendation system, which takes into account the health information of citizens and their preferences, combines them with the real-time information about weather and air condition collected from smart city sensors and recommends personalized path alternatives that better fit to each end-user profile. The 'Motivate' CAR system (Lin et al, 2011) used several recommendations (e.g. take a break from work, stretch, walk, cycle to a park, go to a museum, etc) that promote social, physical and mental balance and considered various context parameters including: location, user agenda, weather, user profile and time. 'Let's exercise' (Gupta et al, 2016) is another CAR system that recommends physical activities, whereas more approaches for motivating older people to engage in social and physical activities are presented in (Ponce et al, 2015), which also proposes a CAR system for suggesting social and other events that match people profile. Biosensors can take CARS to the next level, by introducing an additional context, the psychological one. The detection of stress and arousal can improve the recommendations' timing and increase their acceptance ratio.

4.3. Security and privacy enablers

Basic security tasks such as mutual authentication, encryption, and data integrity remain challenging in IoT. Encryption using elliptic curves and signatures has been shown to be possible on embedded devices but may not be possible on every sensor or actuator (Bauer, 2016). Confidentiality and integrity protection mechanisms also require strong authentication and authorization mechanisms. This requires assigning an identity to sensors and actuators, i.e. a sensor must store some secret to authenticate to a field device. In the past, this was, for example, solved with a second channel and user involvement (Marktscheffel et al., 2016) or using certificates (Hummen et al., 2013). However, all these solutions lack scalability and support for dynamic, unobtrusive smart environments. Concerning security and privacy at the backend, since smart healthcare applications will require distribution of sensitive data and its processing, they will need to adopt new distributed and/or collaborative paradigms of cloud computing. The obfuscation and anonymization of uploaded data (Bentounsi, et al., 2012) is a simple technique to prevent sensitive information leakage, which however affects the data and makes it unusable for other applications. Fully homomorphic encryption (Gentry, 2009), privacy preserving encryption (Li et al, 2013) and attribute-based encryption (ABE) have been proposed for encrypting sensitive user data, without limiting the functionality of cloud applications. However, cryptography alone cannot sufficiently preserve user privacy and thus other forms of privacy enforcement must be employed (Van Dijk and Juels, 2010), such as proper identity and authorization management, by specifying and enforcing security, access control, and privacy policies. Indeed, an ENISA report (ENISA, 10) on security and resilience of e-Health infrastructures and services, identifies that access control is a very significant priority in securing applications. Among the studied authorization schemes proposed for systems with different requirements and properties, a cross-platform solution that meets the requirements of all types of embedded systems and provides interoperability is the eXtensible Access Control Markup Language (XACML) (Parducci, 2013), the de-facto standard for specifying and evaluating access control policies (Liu et al., 2011), also supporting its extension with privacy-aware features (Rissanen, 2015).

Another important aspect that is related to the above and raises significant concerns is the interplay between machine learning techniques and privacy. More specifically, there is a recent trend to design Machine Learning models that are trained from IoT data and this raises many privacy concerns, as well as several ethical issues. When the data used to train the models comprises unfiltered data from the real world, then there is the risk to learn the respective behaviors that exist in the data, and this may result to strange or unethical behaviors. The research on security and privacy of BDA models still devotes less attention to the impact of similar solutions that assume distributed architectures and BDA models for IoE (Damiani et al, 2018). Several researchers agree that the best trade-off between utility and disclosure risk can be found at model inference time, when there exist real data to evaluate the data utility and the impact of its disclosure rather when estimating the risk a priori (Jia et al., 2018). BDA pipeline modules are owned and managed by multiple operators, each with its own interests and agenda; therefore, we cannot always postpone all disclosure control to analytics computation time. In this context, non-interactive randomization at data acquisition time, while decreasing utility, can provide maximum flexibility and best accommodate provisions for compliance with regulations, ethics and cultural factors.

Considering the above, to address the security and privacy concerns, a state of the art IoT/IoMT healthcare solution must combine novel and standardized technologies to provide lightweight and usable mechanisms for the authentication of its entities (devices, applications, users etc.) and the protection of their resources through strong, unambiguous and fine-grained authorization services. The XACML authorization engine can form the basis of this endeavor, developing dynamic authorization services and providing the necessary variables (operational or situational context, as well as privacy requirements and other scenario/use case peculiarities). Privacy-aware features can be embedded into the policy definitions. Developed solutions for the back-end security must allow the creation of secure and privacy-preserving communications within and from the cloud infrastructure to the smart home instance, as well as the healthcare service providers in an end-to-end manner. The privacy controls implemented can also include differential privacy and selective data obfuscation and randomization, both for raw data and for outcomes of the data analytics, learning and evolution processes. The combination of the above guarantees and visibility of the system's status, and consequent enhanced operator control and accountability, the platform must provide a significantly higher level of security and privacy than what is currently available in the domain, to unambiguously alleviate the pertinent concerns.

5. Smart healthcare applications – state of the art research efforts

Within the landscape sketched in the previous sections, and motivated by the significant benefits of IoT/IoMT-enabled smart healthcare applications, there is a plethora of efforts driven by the research and industry communities that aim to overcome the associated challenges and realize the full potential of these technologies towards improving the health, well-being and independent living of patients and the elderly (Haghi et al., 2017; Zhu et al., 2015; Chaaraoui et al., 2012). In this context, the following subsections highlight some state of the art research efforts on the topic, presenting three research projects that have recently started or will soon start tackling said issues, each proposing a novel approach and investigating different angles of the IoT/IoMT-enabled smart healthcare landscape. More specifically, the presented projects include SMART BEAR, sustAGE and XVIepsis.

5.1. SMART BEAR – smart living solution platform for the elderly

The SMART BEAR project aims to provide an intelligent and personalized digital solution for sustaining and extending healthy and independent living by implementing an affordable, accountably secure and privacy-preserving innovative platform with off-the-shelf smart and medical devices to support the healthy and independent living of elderly people with five prevalent health-related conditions, namely hearing loss, cardiovascular diseases, cognitive impairments, mental health issues and balance disorders, as well as frailty. This will be achieved through intelligent, evidenced-based interventions on lifestyle, medically-significant risk factors, and chronic disease management, enabled by the utilization of continuous and objective medical and environment sensing, assistive technologies and big data analytics.

In more detail, the SMART BEAR platform integrates heterogeneous sensors, and assistive devices that collect and analyze data streams from the elderly activities and modules that extract the necessary evidence to design personalized interventions that promote healthy and independent living. The platform will also be connected to hospital and other healthcare service systems to obtain data specific to the end users (e.g., medical history), that will need to be considered in making decisions for interventions. SMART BEAR will leverage big data analytics and learning capabilities, allowing for large scale analysis of the above mentioned collected data, to generate the evidence required for making decisions about personalized interventions. Privacy-preserving and secure by design data handling capabilities, protecting data at rest, in processing, and in transit, will cover comprehensively all the components and connections utilized by the SMART BEAR platform. An overview of the SMART BEAR platform is depicted in **Figure 1**. To achieve the above, SMART BEAR will build on the platform developed within the H2020 project EVOTION (http://h2020evotion.eu/) to support evidence based public health policies formation and monitoring. The EVOTION platform supports: a) the continuous collection of medical, physiological and lifestyle data from heterogeneous resources including hospitals, biosensors, advanced hearing aids and mobile phones and b) the analysis of these data, driven by high level big data analytics and decision models to generate evidence useful for making public health policy level interventions (Ye et al., 2018; Aniseti et al., 2018; Prasinos et al., 2017). The EVOTION platform is currently used in 5 hospitals in Greece and the UK, collecting real-time data from more than 1000 hearing aid users.

Key areas of innovation for SMART BEAR will include:

1) Integration with IoT enablers and platforms (e.g. FI-WARE, Copernicus, consumer smart ecosystems), SMART BEAR will extend the connectivity of the EVOTION platform to support new medical devices, wearables, smart home/IoT sensors and actuators, and smart environment infrastructures;
2) development of new high level data analytics and decision models to support the intelligent and personalized interventions required for enhancing the healthy and independent living of the elderly;
3) integration of the EVOTION platform with a continuous security and privacy assurance platform to provide the continuous auditability and transparency needed for ensuring the SMART BEAR platform's trustworthiness by its end users, and;
4) testing and validation of the above at a much greater scale, involving 5.000 participants across 5 countries.

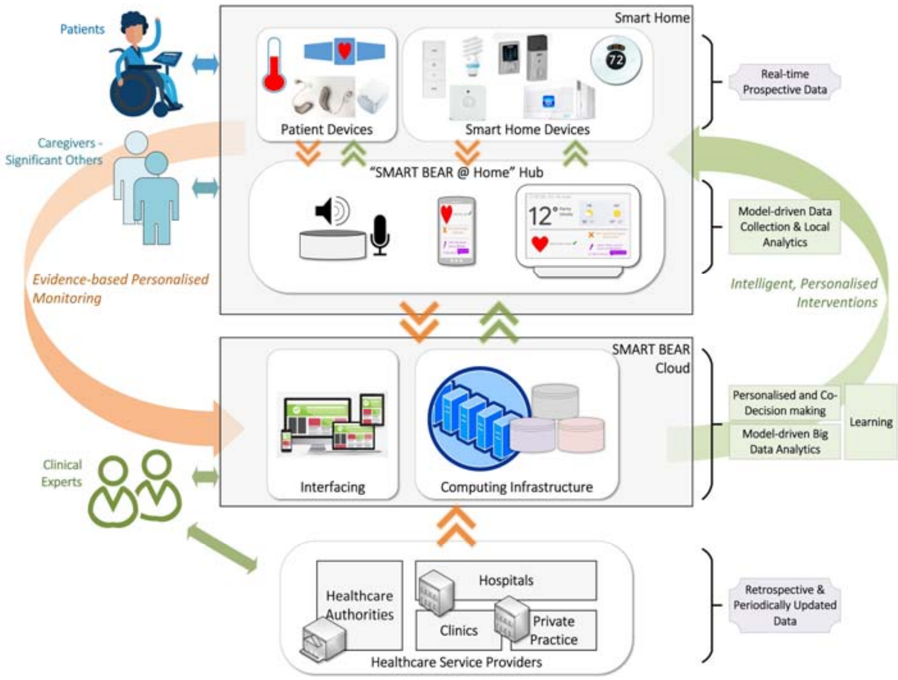

Figure 1. The SMART BEAR concept

In developing the above extensions, special consideration will be given to creating an extensible and sustainable platform, open for wider adoption in the connected health ecosystem.

5.1.1. Targeted Pilot Environments

The SMART BEAR platform will be tested and validated through five large scale pilots, involving 5.000 elderly users living at home in Greece, Italy, France, Spain, and Romania. The pilots will enable the evaluation of the platform in the context of healthcare service delivery by private and public providers at regional, state and EU level, and demonstrate its efficacy, extensibility, sustainability, and cost effectiveness for the individual and the healthcare system. SMART BEAR will benefit from this diversity as data coming from all pilots will be collected and evaluated.

More specifically, the Greek pilot will run in two regions with different characteristics in order to evaluate the efficiency of the SMART BEAR solution in different socioeconomic conditions. These will be the Municipality of Palaio Faliro (a metropolitan area with an estimate of approximately 10.000 people being over 65 years of age) and the Region of Peloponnese (a rural area with a significant portion of elderly population). The Italian pilot will cover both rural and urban territories in

Lombardy, so as not to restrict the sampling of this pilot to a single geographical area. Two areas are covered by the pilot: the metropolitan area of Milan (8.2 million inhabitants over an area of about 13,000 km2) and the District of Crema (150.000 inhabitants over an area of about 573 km2). The two areas are very different because of their extent, environmental conditions, urban services, and population. Concerning the French pilot, two regions are considered as possible and interesting experimentation areas: i) Île-de-France (the Paris region), the area with the largest number of elderly people (and thus, of dependent elderly people); ii) Nouvelle Aquitaine (particularly the “Creuse” department), the region where the population is the oldest, and where many innovative e-health programs and projects are developed for elderly people and iii) Bretagne, where the elderly people are the healthiest, and which is an innovative and dynamic region in the e-health field. In the Spanish pilot, the focus will be on the Basque Country, spanning an area of about 7,000 km2 with 2 million inhabitants, and being one of the European regions most affected by the ageing process. The pilot will cover independent elderly users living at home, seniors living in rural areas, as well as those living in collective structures, such as senior residences. Finally, in terms of the Romanian pilot, participants will come mainly from the capital Bucharest, with a population of about 2 million people, of which 17% are over 65 (359,182). Bucharest is the area with both the largest number of elderly people (3 times higher than in any other administrative region of the country), and the largest number of dependent elderly people.

5.1.2. The SMART-BEAR Consortium

SMART BEAR participants collectively constitute a consortium capable of achieving the project objectives and both well-suited and committed to the tasks assigned to them. The SMART BEAR consortium consists of 25 organizations, including 4 big industry partners in the ICT domain (ATOS Spain S.A. from Spain; Philips Electronics Nederland B.V. from Netherlands; International Business Machines Corporation from Israel, and; Lombardia Informatica from Italy). Moreover, the SMART BEAR consortium includes 5 partners from the healthcare domain (Comunita' Sociale Cremasca and the Fondazione Centro San Raffaele from Italy;

CATEL from France; MUTUALIA from Spain, and; Fundatia Ana Aslan International from Romania), as well as 2 local authorities (Region of Peloponnese and Municipality of Palaio Faliro from Greece). Part of the consortium are also 8 large academic/research organizations (CNR ICAR from Italy; Foundation for Research and Technology–Hellas, National Kapodistrian University of Athens, and University of Ioannina from Greece; Università degli Studi di Milano from Italy; Universidad del País Vasco/ Euskal Herriko Unibertsitatea from Spain; City, University of London from the United Kingdom, and Institute of Communication & Computer Systems from Greece) as well as 6 SMEs (Sphynx Technology Solutions AG from Switzerland, StreamVision from France, IT Support Solutions from Romania, Innovatec from Spain, Athens Technology Centre from Greece, and Bird and Bird from the United Kingdom). All these providers bring in not only their technological expertise but also their entrepreneurial aspiration regarding their role in creative industries.

5.2. sustAGE – Smart environments for person-centered sustainable work and well-being

sustAGE (https://www.sustage.eu/) is a person-centered smart solution that aims to promote the concept of "sustainable work" for EU industries, thus support the well-being, wellness at work and productivity of ageing employees through three main dimensions. The first dimension is directed towards improving occupational safety and health via risk assessment and prevention strategies based on workplace and person-centered health surveillance monitoring. The second dimension aims to promote the wellbeing of employees via personalized recommendations for physical and mental health improvement and the third dimension supports decision making related to task/job role modifications aiming to optimize the overall workforce productivity by assessing the abilities of individual persons (e.g. physical, mental, social) in relation to work demands and risks. The sustAGE solution explores two industry domains with significant challenges and requirements, specifically a) manufacturing, and b) transportation & logistics.

5.2.1. The industry domains

The case of assembly line workers in the Automotive Industry

There are hundreds of tasks in the manufacturing assembly process, which differ in terms of posture, workload and complexity, and require both manual labor as well as significant cognitive workload. In automotive industry, assembly lines can produce 2-3 different models of a vehicle, each with dozens of possible variations. There is a small tolerance for errors in an often-customizable production unit; therefore, workers need to be constantly aware of the specific order and customizations needed to be made. Furthermore, to choose the best match between task and worker in both repetitive short-cycle task operations and complex tasks, worker profiling on an individual and frequent basis, is necessary to assess a worker's physical abilities and mental skills. To further take into account age-related changes, it is important to monitor both the environment conditions, the worker's health state and actions to derive information on individual's workload that may further impact their physical and mental state. Actions to be monitored comprise of user proximity to critical areas, repetitive movements, bend or twisted postures, pushing/pulling/lifting an object, along with the temporal aspects of the action, e.g. time to complete the action, pace, etc.

The case of port workers in Transportation & Logistics Industry

Port work activities involve loading procedures, unloading, transport and storage of goods, such as container movement and roll on/roll off, as well as pilotage, workboat and tug operation, ship repairs, vessel traffic management and similar marine activities. Dock workers are usually exposed to stressful and dangerous working conditions. Commonly shift work (morning, afternoon, night) can impact in sleep deprivation, misalignment of circadian rhythms, drowsiness and performance deficits. Noise, vibrations, dust, wind and tide are commonly occurring in ports. Workers who perform handwork and require physical strength to carry out activities are prone to musculoskeletal disorders. Beyond the physical extent of the port work, the mental aspect, in relation to the demand of attention and concentration at work, is important as workers need to be continuously alert. The main case of interest in sustAGE regards the loading/unloading procedures of containers, in which the system monitors the container crane operator, the workers involved in the loading/unloading procedures as well as other moving objects/humans in proximity to the crane during maneuvering. The actions to be detected in this case to further support the analysis, profiling and recommendations of the system are fatigue as derived by tracked movements along with temporal properties, as well as physiological measurements and proximity of workers to critical areas and moving objects.

5.2.2. IoT ecosystem and system functionalities

The developed system functionalities build upon an IoT ecosystem, based on off-the-shelf sensors integrated in daily devices and in the work environment, considering both indoor (manufacturing) and outdoor (port) working conditions. The system gathers contextual information from the working environment and from users' physiological signals, tasks, activities and behavioral patterns, in order to support user profiling and provide personalized recommendations for better managing health, wellness and safety. The sustAGE technology will consider information-rich micro-moments[9] (a highly investigated topic of leading technology companies like Google, Microsoft, Facebook, geared to be the "next big thing" in intelligent system design) to process the short- and long-term aspects of symbiotic interaction, to identify patterns of human behavior, draw correlation between actions, predict what humans do and don't want, improve user's acceptance and engage users in a successful long-term interaction. Therefore, the notion of time, the consideration of real world phenomena and interactions in association with the course of time is very important. Measurements collected from different devices and modules of the system support the definition of key micro-moments for future user profile updates, recommendations and notifications. Different micro-moments related to the user daily schedule, work environment, workload, physical/emotional/mental state and social activities are used (**Table 2**).

Table 2. List of indicative micro-moments

Category	Indicative list of micro-moments

[9] https://www.thinkwithgoogle.com/marketing-resources/micro-moments/

Work environment	High/low temperature, noise level, pollution, wet/dry weather
Work/Task	Work shift, task onset, task completion, task type (repetitive work, bent or twisted body posture), push/pull an object, lifting heavy load, task switch, pace, task break, injury from accident/body part
Daily schedule	Arriving at-leaving from work, lunch/dinner, medication intake, wake-up, go to sleep, meet friends
Physical	Health check, instance of pain, high/low pulse rate, body temperature, walking, resting, steps count during activity, fatigue
Mental	Stress/frustration, depression sign, emotional state changes, state communication/verification by the system
HR	Sick days, tasks increasing/decreasing productivity, employee requests for task changes

Indicative key features of the sustAGE solution are:

- *Monitoring of user actions and behaviors in work environment and personal life*. An IoT ecosystem is exploited, comprising of smart sensors and mobile devices for locating and tracking users in real-time and for the fine-grained detection of user actions and states. By combining information from multiple sources, the system will be able to support user profiling in a privacy-preserving manner and provide context-aware recommendations and analytics.
- *Abstraction and episodic knowledge*. Analyze users' activities and memorize important episodes aiming to keep important information related to past human activities and states. Building on users' micro-moments, the system will memorize actions that users need to do and will better predict user reactions by considering their activity in similar past situations.
- *Multi-aspect user profiling*. The aggregation of past user-specific knowledge, comprising of user preferences, the results of user performance in work- and training-related activities and long-term abstractions will allow a more complete physical, mental and psychosocial user profiling. The collection and analysis of related information will be done transparently, without user intervention.
- *Multi-level personalized recommendations.* Recommendations with respect to three different levels are provided, namely physical, mental and workforce. Recommendations on the first two will be managed by the individual person measuring the impact on the work-ability, health and well-being, whereas the

workforce recommendations will be managed by the management. The system will consider spatio-temporal aspects, taking into account the user's activity, state, time and location, the daily and weekly schedule and recommend an activity at the right moment.

- *Safe working environment.* Continuously monitor both the environment conditions in the working area (i.e., manufacturing floor or port dock) and workers' health related signs, in order to early detect critical cases and workload to provide alerts to specific workers, who must take short breaks or switch task for the rest of their shift or over longer intervals.

The IoT infrastructure comprises of the following devices/sensors:

- *Environmental sensors* measuring air temperature, humidity, air quality, pressure, dust concentration and noise based on Raspberry Pi/Arduino custom sensors that are open source, low cost, accurate and durable.
- *Cameras* installed in key working areas. For the manufacturing indoor environment of the assembly line, passive stereo cameras are used to monitor postures and repetitive actions of users whereas for the port outdoor environment, monocular cameras with varying focal lengths are used to monitor crane operators and workers involved in loading/unloading of containers and people/objects in the vicinity of the crane.
- For localization in indoor environments, *beacons* achieve a precision of up to 10-20 cm within a range of up to 100m, whereas for outdoor environments the *GNSS receivers* built-in smartphones are used.
- *Wristwatch device* gathering physiological measurements, able to trigger notifications to users from the system. The selected device should offer SDKs and APIs to facilitate its programmability and access to the data.
- *Smartphone* devices able to support Galileo, offering centimeter accuracy and ability to communicate with the wristwatch device.

The above set of devices/sensors can collaboratively provide information on different user activities/actions (e.g. walking, bend, stand/sit, push/pull object), state (e.g. fatigue, discomfort) integrating temporal aspects and on detecting specific events in the environment (e.g. user monitoring in specific areas, proximity to hazardous conditions). Moreover, the smartphone is the primary device for communication and multimodal interaction supporting natural language understanding and sentiment analysis. The adopted IoT configuration exhibits the advantages of unobtrusive user-context interaction monitoring in a privacy-preserving way considering that in private life, outside the working environment, only the wristwatch and the mobile device are to be used. The system supporting raw data processing near the end-devices to prevent potentially privacy-sensitive information to be sent to the upper layers of the platform in the cloud.

5.2.3. The sustAGE Consortium

The sustAGE consortium comprises a unique blend of partners from disciplines that span a broad spectrum. The project brings together one of the largest European automotive industries (Centro Ricerche Fiat Scpa, Italy), one of Greece's most important maritime ports (Heraklion Port Authority, Greece), a global leader in ICT products and services (Software AG, Germany), SMEs providing expertise in interactive technologies for e-Health (Imaginary Srl., Italy) and distributed systems (AEGIS IT Research UG, Germany), three top European universities in the areas of Embedded Intelligence for Health Care and Wellbeing (University of Augsburg, Germany), Ageing and Neurodegenerative Diseases (Universidad Nacional de Educación a Distancia, Spain) and Positioning and Sensors (Aristotle University of Thessaloniki, Greece) and two top European research centers in the areas of Ergonomics, working environments and human factors (Forschungsgesellschaft für Arbeitsphysiologie und Arbeitsschutz E.V.) and emerging ICT research (Foundation for Research and Technology–Hellas).

5.3. XVlepsis – An intelligent non-invasive biosignal recording system for infants

Over the last years there is a strong interest in improving patient monitoring in an attempt to facilitate clinicians providing error prone decisions while saving time and improving the overall quality of patient care. Such approaches are particularly useful in time critical settings, such as the intensive care unit (ICU) of the hospital. A stronger effort is required to provide multimodal real-time neonate monitoring platforms of high quality being ubiquitous and non-obstructive while at home.

xVLEPSIS (https://xvlepsis.gr/en) is an advanced system for the prediction of potentially hazardous events related to infants. As many pathological situations can occur during an infant's night sleep which can potentially be threatening to health if not detected promptly, there is an imperative need for early detection of medical emergencies during infant sleep, through an unobtrusive and non-invasive detection system. Invasive devices and sensors could disrupt the infant's sleeping phases that are extremely important for their development and degrade the quality of their rest.

xVLEPSIS uses a scalable system comprising a 'smart' bed mattress and a camera positioned to monitor the infant cradle, and without disturbing the infant's sleep it can detect possible pathological conditions.

5.3.1. Integration of smart biosignal sensors in a detection system for hazardous conditions

The xVLEPSIS system will entangle diverse user-friendly electronic smart sensors, integrated under a 'smart' mattress, in combination with a high-resolution baby monitor. In brief, the following bio-signals will be recorded, analyzed and investigated for their applicability as biomarkers for certain pathologies:

- Video recording using a high-resolution camera and audio recording using a microphone of high definition.
- Ballistocardiogram (BCG) (Giovangrandi et al., 2011) recording, which records sudden blood ejections into the great vessels with each heartbeat using pressure sensors under the bed mat and generates a plot that represents repetitive body movements during sleep.
- Temperature and humidity detection using suitable sensors under the bed mat.

The development of an intelligent system that will detect potentially hazardous pathological conditions, with the use of sophisticated machine learning techniques will lead to:

I. a mobile or smart watch based notification system, that will alert the parents in the case of emergency, and

II. the continuous bio-signal recording, throughout the infant's sleep. The recorded data could be sent to the doctor or the hospital, in the case an abnormality is detected, or they could be evaluated by the doctor during regular infant examination, in the case nothing critical is detected. Therefore, the pediatrician will be able to examine and evaluate all the available medical data and detect any incidents that may have occurred at night without having been perceived by the parents.

Many advantages arise from the development of a low-cost product with all the aforementioned features:

- Continuous recording of high definition video and audio will allow for a more effective monitoring of the infant, whereas the pathological situations detection system will lead to the discovery of incidents that would otherwise remain unnoticed.
- The proposed non-invasive monitoring system will aid the diagnosis and proper treatment of medical disorders that can occur while the parents are not present, e.g. febrile convulsions, epileptic seizures or apnea.
- Pediatricians always face the challenge to evaluate medical incidents solely based on the information that parents provide, which is not objective and accurate, especially during the first year of infants life. The proposed integrated system offers the medical professionals in charge the opportunity to assess those incidents based on detailed recorded bio-signals and, thus, form a better opinion on the diagnosis.
- The use of innovative machine learning algorithms performed on the multimodal medical signals will significantly aid the detection of new quantitative biomarkers of the relevant diseases.
- The medical database that will be implemented will significantly contribute to the research and study of such early childhood disorders.

Such a system is expected to effectively notify the parents and enable doctors to identify specific pathologies. The system will continuously and unobtrusively record important bio-signals and analyze them using sophisticated machine learning algorithms, suitable for pathology-specific pattern identification and biomarker extraction. The software to be developed will act as a recommendation and alarming system notifying the parents and/ or the physician, if needed, by means of a notification center hosted in a smartphone and/ or a smartwatch. A dedicated repository will host raw signals for future reference or doctor's referral.

6. Conclusions and future directions

The role of smart biosensors and IoT is significant in modern medical care and patients, care-providers and health professionals can strongly benefit from smart applications developed on top of such infrastructures. In this chapter, we presented the challenges and opportunities from the application of smart biosensors in healthcare and we described three state-of-the-art solutions that employ smart sensors in this context. The applications demonstrate how smart living solutions can be developed on top of an ecosystem that combines IoT and smart biosensors, that record and analyze bio-signals in a non-invasive way and allow the early detection and prevention of potentially hazardous pathological conditions. Since there are still many challenges concerning data privacy, data aggregation and integration and intelligent decision making to be overcome, this effort has to be intensified towards the use of data analysis and data mining techniques as well as the development of machine learning models that can efficiently handle bio-signal data streams and effectively decide on the proper actions to take.

Acknowledgements

This work has been partially supported by the European Union's Horizon 2020 Research and Innovation programme under Grant Agreements No. 857172 (EU project SMART BEAR) and No. 826506 (EU project sustAGE). Also, this work has been partially supported by the European Union and Greek national funds through the Operational Program Competitiveness, Entrepreneurship and Innovation, under the call Research – Create – Innovate (project XVlepsis, T1EDK-04440).

References

Ajami, S. and Teimouri, F. (2015). Features and application of wearable biosensors in medical care. *Journal of Research in Medical Sciences*. 20(12):1208–1215. doi:10.4103/1735-1995.172991

Anisetti, M., Ardagna, C., Bellandi, V., Cremonini, M., Frati, F., & Damiani, E. (2018). Privacy-aware Big Data Analytics as a service for public health policies in smart cities. *Sustainable cities and society*, *39*, 68-77.

Bauer, J., Staudemeyer, R. C., Pöhls, H. C. and A. Fragkiadakis, A. (2016). ECDSA on things: IoT integrity protection in practice. In *Proc. of Information and Communications Security (ICICS 2016)*, Springer.

Bentounsi, M. Benbernou, S. and Atallah, M. J. (2012). Privacy-preserving business process outsourcing," in *Proc. IEEE 19th International Conference on Web Services*, pp. 662–663.

Brush, A.B, Lee, B., Mahajan, R., Agarwal, S., Saroiu, S. and Dixon, C. (2011). Home automation in the wild. In *Proc. 2011 annual conference on Human factors in computing systems - CHI '11*, p. 2115, New York, USA, ACM Press. ISBN 9781450302289. doi: 10.1145/1978942.1979249.

Carroll, E. A., Czerwinski, M., Roseway, A., Kapoor, A., Johns, P., Rowan, K., & Schraefel, M. C. (2013). Food and mood: Just-in-time support for emotional eating. In *2013 IEEE Humaine Association Conference on Affective Computing and Intelligent Interaction* (pp. 252-257).

Casino, F., Patsakis, C., Batista, E., Borràs, F., & Martínez-Ballesté, A. (2017). Healthy routes in the smart city: A context-aware mobile recommender. *IEEE Software*, *34*(6), 42-47.

Chaaraoui, A.A., Climent-Pérez, P., Flórez-Revuelta, F. (2012). A review on vision techniques applied to Human Behaviour Analysis for Ambient-Assisted Living. *Expert Systems with Applications*, 39(12):10873-10888. doi:10.1016/j.eswa.2012.03.005

Chowhan, J., Denton, M., Brookman, C., Davies, S., Sayin, F. K., & Zeytinoglu, I. (2019). Work intensification and health outcomes of health sector workers. *Personnel Review*, 48(2), 342-359.

Da Cruz, M.A.A., Rodrigues, J.J.P.C., Al-Muhtadi, J., Korotaev, V.V., and de Albuquerque, V.H.C. (2018). A Reference Model for Internet of Things Middleware. *IEEE Internet of Things Journal*, 5(2):71-883. doi: 10.1109/JIOT.2018.2796561

Damiani, E., Gianini, G., Ceci, M., & Malerba, D. (2018). Toward IoT-Friendly Learning Models. In *IEEE 38th International Conference on Distributed Computing Systems (ICDCS)* (pp. 1284-1289).

Dias D, Paulo Silva Cunha J. (2018). Wearable Health Devices-Vital Sign Monitoring, Systems and Technologies. *Sensors*, 18(8):2414. doi:10.3390/s18082414.

Driscoll, D., Mensch, A., Nixon, T. and Regnier A. (2009). Devices profile for web services, version 1.1. URL http://docs.oasis-open.org/ws-dd/dpws/wsdd-dpws-1.1-spec.pdf

Van Dijk, M. and Juels, A. (2010). On the Impossibility of Cryptography Alone for Privacy-preserving Cloud Computing, in *Proc. 5th USENIX Conference on Hot Topics in Security*, pp. 1–8.

EIPAHA - European Innovation Partnership on Active and Healthy Ageing (2012). A compilation of good practices on Prevention and Early Diagnosis of Frailty and Functional Decline, Both Physical and Cognitive in Older People, European Union, Brussels, Belgium. Available at: https://ec.europa.eu/research/innovation-union/pdf/active-healthy-ageing/gp_a3.pdf

ENISA (2015). Security and Resilience in eHealth Infrastructures and Services.

Feichtenhofer, C., Pinz, A. and Zisserman, A. (2016). Convolutional two-stream network fusion for video action recognition. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, p. 1933-1941.

Frankle, J., and Carbin, M. (2018) The lottery ticket hypothesis: Finding sparse, trainable neural networks. https://arxiv.org/abs/1803.03635.

Fysarakis, K., Papaefstathiou, I., Manifavas, C., Rantos, K. and Sultatos, O. (2014). Policy-based access control for DPWS-enabled ubiquitous devices. In *Proc. 2014 IEEE Emerging Technology* *and Factory Automation (ETFA)*, pages 1–8, Barcelona, Spain. IEEE. ISBN 978-1-4799-4845-1. doi: 10.1109/ETFA.2014.7005233.

Gentry, C. (2009). Fully Homomorphic Encryption Using Ideal Lattices, in *Proc. Forty-first Annual ACM Symposium on Theory of Computing*, pp. 169–178.

Giovangrandi, L., Inan, O. T., Wiard, R. M., Etemadi, M., & Kovacs, G. T. A. (2011), "Ballistocardiography – A Method Worth Revisiting". Proc. *IEEE Eng Med Biol Soc*, pp. 4279–4282.

Gomes, Y.F., Santos, D. F. S, Almeida, H. O. and Perkusich, A. (2015). Integrating MQTT and ISO/IEEE 11073 for health information sharing in the Internet of Things. In *2015 IEEE International Conference on Consumer Electronics (ICCE)*, pages 200–201. ISBN 978-1-4799-7543-3. doi: 10.1109/ICCE.2015.7066380.

Gupta, S., Sood, S. P., & Jain, D. K. (2016). 'Let's Exercise': A Context Aware Mobile Agent for Motivating Physical Activity. In *Emerging Research in Computing, Information, Communication and Applications* (pp. 511-520). Springer, New Delhi.

Haghi, M., Thurow, K., Stoll, R. (2017). Wearable Devices in Medical Internet of Things: Scientific Research and Commercially Available Devices. *Healthc. Inform. Res.* 23(1):4-15. doi:10.4258/hir.2017.23.1.4

Henriksen, A., Haugen Mikalsen, M., Woldaregay, A.Z., et al. (2018). Using Fitness Trackers and Smartwatches to Measure Physical Activity in Research: Analysis of Consumer Wrist-Worn Wearables. *J. Med. Internet. Res.* 20(3):e110. doi:10.2196/jmir.9157

Hummen, R., Ziegeldorf, J. H., Shafagh, H., Raza, S., & Wehrle, K. (2013, April). Towards viable certificate-based authentication for the internet of things. In *Proc. 2nd ACM workshop on hot topics on wireless network security and privacy* (pp. 37-42). ACM.

Ilarri, S., Hermoso, R., Trillo-Lado, R., & Rodríguez-Hernández, M. D. C. (2015). A review of the role of sensors in mobile context-aware recommendation systems. *International Journal of Distributed Sensor Networks*, *11*(11), 489264.

Jekel, K., Damian, M., Wattmo, C., Hausner, L., Bullock, R., Connelly, P.J., Dubois, B., Eriksdotter, M., Ewers, M., Graessel, E., Kramberger, M.G., Law, E., Mecocci, P., Molinuevo, J.L., Nygård, L., Olde-Rikkert, M.G., Orgogozo, J.M., Pasquier, F., Peres, K., Salmon, E., Sikkes S.A., Sobow, T., Spiegel, R., Tsolaki, M., Winblad, B. and Frölich, L. (2015). Mild cognitive impairment and deficits in instrumental activities of daily living: a systematic review. *Alzheimer's research & therapy*, 7(1):17.

Jeong, I. C., Bychkov, D. and Searson, P. C. (2019). Wearable Devices for Precision Medicine and Health State Monitoring. *IEEE Transactions on Biomedical Engineering*. 66(5):1242-1258. doi:10.1109/TBME.2018.2871638

Jia, Q., Guo, L., Jin, Z., & Fang, Y. (2018). Preserving Model Privacy for Machine Learning in Distributed Systems. *IEEE Transactions on Parallel and Distributed Systems*. 29(8):1808-1822. doi: 10.1109/TPDS.2018.2809624

Khan, W.Z., Xiang, Y., Aalsalem, M.Y. and Arshad, Q. (2013) Mobile phone sensing systems: A survey. *IEEE Communications Surveys Tutorials* 15(1), 402–427.

Kim, S.-M., Choi, H.-S. and Rhee, W.-S. (2015). IoT home gateway for auto-configuration and management of MQTT devices. In *2015 IEEE Conference on Wireless Sensors (ICWiSe)*, pages 12–17. ISBN 978-1-4673-9398-0. doi: 10.1109/ICWISE.2015.7380346.

Kim, E. Helal, S. Cook, D. (2010) Human activity recognition and pattern discovery, *IEEE Pervasive Computing* 9(1) 48–53.

Kumar, A., Kim H., and Hancke, G.P. (2013). Environmental Monitoring Systems: A Review. IEEE Sensors Journal 13(4):1329-1339. doi: 10.1109/JSEN.2012.2233469

Leto, L., & Feola, M. (2014). Cognitive impairment in heart failure patients. *Journal of geriatric cardiology: JGC*, *11*(4), 316.

Li, M., Yu, S., Ren, K. Lou, W. and Hou, Y.T. (2013). Toward privacy-assured and searchable cloud data storage services, *Network*, IEEE, vol. 27, no. 4, pp. 56–62.

Lin, Y., Jessurun, J., De Vries, B., & Timmermans, H. (2011). Motivate: Towards context-aware recommendation mobile system for healthy living. In *2011 5th IEEE International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops* (pp. 250-253).

Liu, A. X. Chen, F., Hwang, J. and Xie, T. (2011). Designing fast and scalable XACML policy evaluation engines. *IEEE Transactions on Computers*, 60(12):1802–1817, 2011. ISSN 00189340. doi: 10.1109/TC.2010.274

Madkour M., Benhaddou D., and Tao C. (2016). Temporal data representation, normalization, extraction, and reasoning: A review from clinical domain, *Comput Methods Programs Biomed.*128: 52–68.

Mehrotra P. (2016). Biosensors and their applications – A review. *J Oral Biology and Craniofacial Research* 6(2): 153–159. doi: 10.1016/j.jobcr.2015.12.002

Marktscheffel, T., Gottschlich, W., Popp, W, Werli, P. Fink, S.D., Bilzhause, A. and de Meer, H. (2016). QR Code Based Mutual Authentication Protocol for Internet of Things. In Proc. *IEEE 5th workshop on IoT-SoS: Internet of Things Smart Objects and Services (WOWMOM SOS-IOT 2016)*.

Mendelson Y., Dao D.K., Chon K.H. (2013). Multi-channel pulse oximetry for wearable physiological monitoring; Proceedings of the 2013 IEEE International Conference on Body Sensor Networks (BSN); MA, USA, USA. 6–9 May 2013; pp. 1–6.

Mois, G., Folea, S., Sanislav, T. (2017), Analysis of three IoT-based wireless sensors for environmental monitoring, *IEEE Trans. Instrum. Meas.*, vol. 66, no. 8, pp. 2056-2064.

Murad, K., & Kitzman, D. W. (2012). Frailty and multiple comorbidities in the elderly patient with heart failure: implications for management. *Heart failure reviews*, 17(4-5), 581-588.

Parducci, B. Lockhart, H. and Rissanen, E. (2013). eXtensible Access Control Markup Language (XACML) Version 3.0,

Ponce, V., Deschamps, J. P., Giroux, L. P., Salehi, F., and Abdulrazak, B. (2015). QueFaire: Context-aware in-person social activity recommendation system for active aging. In *International* Conference on Smart Homes and Health Telematics (pp. 64-75). Springer, Cham.

Poppe R. (2010). A survey on vision-based human action recognition, *Image and Vision Computing*, 28(6):976-990. doi: 10.1016/j.imavis.2009.11.014

Prasinos, M., Spanoudakis, G., & Koutsouris, D. (2017). Towards a model-driven platform for evidence based public health policy making. In Proc. *29th Intl. Conf. on Software Engineering and Knowledge Engineering*.

Raghupathi W., and V. Raghupathi V. (2014). Big data analytics in healthcare: promise and potential. *Health Information Science and Systems* (2-3).

Ranjan, Y., Kerz, M., Rashid, Z., Böttcher, S., Dobson, R.J., and Folarin, A.A, (2018). Radar-base: A novel open source m-health platform. In: *Proc. ACM Intel. Joint Conf. and 2018 Intl. Symposium on Pervasive and Ubiquitous Computing and Wearable Computers, UbiComp '18*, pp. 223–226.

Razzaque, M.A., Milojevic-Jevric, M., Palade, A., and Clarke, S. (2016). *Middleware for Internet of Things: A Survey*. IEEE Internet of Things Journal, 3(1):70-95. doi: 10.1109/JIOT.2015.2498900

Rissanen, E. (2015) "XACML v3.0 Privacy Policy Profile Version 1.0," OASIS. [Online]. Available: http://docs.oasis-open.org/xacml/3.0/privacy/v1.0/xacml-3.0-privacy-v1.0.html

Shelby, Z., Hartke, K. and Bormann, C. (2014). The Constrained Application Protocol (CoAP). URL https://tools.ietf.org/html/rfc7252.

Sigalas M., Pateraki M., Trahanias P. (2016), Full-body Pose Tracking – the Top View Reprojection Approach. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 38 (8): 1568-1582

Shotton, J., Sharp, T., Kipman, A., Fitzgibbon, A., Finocchio, M., Blake, A., Cook, M. and Moore, R. (2013). Real-time human pose recognition in parts from single depth images. *Commun. ACM* 56(1):116-124. doi:10.1145/2398356.2398381

Xiao-Fei T., Yuan-Ting Z., Poon C.C.Y. Bonato P., (2008). Wearable Medical Systems for p-Health. *IEEE Rev. Biomed. Eng.*1:62–74. doi: 10.1109/RBME.2008.2008248.

Stacey M., McGregor C., (2007). Temporal abstraction in intelligent clinical data analysis: A survey, *Artificial Intelligence in Medicine*, 39(1), 1-24, 2007.

Vayena, E., Dzenowagis, J., Brownstein, J. S., & Sheikh, A. (2018). Policy implications of big data in the health sector. *Bulletin of the World Health Organization*, 96(1), 66–68, 2018

Vos, T., Abajobir, A. A., Abate, K. H., Abbafati, C., Abbas, K. M., Abd-Allah, F., ... & Aboyans, V. (2017). Global, regional, and national incidence, prevalence, and years lived with disability for 328 diseases and injuries for 195 countries, 1990–2016: a systematic analysis for the Global Burden of Disease Study 2016. *The Lancet*, 390(10100), 1211-1259.

WHO (2015). World report on Ageing and Health, World Health Organisation, URL: https://apps.who.int/iris/bitstream/handle/10665/186463/9789240694811_eng.pdf?sequence=1

WHO (2017). Cardiovascular diseases (CVDs) key Facts. World Health Organisation. Available at: http://www.who.int/en/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)

Ye, B., Basdekis, I., Smyrlis, M., Spanoudakis, G., & Koloutsou, K. (2018, March). A big data repository and architecture for managing hearing loss related data. In *2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI)* (pp. 174-177). IEEE.

Zangróniz R, Martínez-Rodrigo A, Pastor JM, López MT, Fernández-Caballero A (2017). Electrodermal Activity Sensor for Classification of Calm/Distress Condition. *Sensors*. 17(10):2324. doi:10.3390/s17102324

Zhu N., et al., Bridging e-Health and the Internet of Things: The SPHERE Project. (2015). *IEEE Intelligent Systems*, 30(4):39-46. doi:10.1109/MIS.2015.57